The Thesis Committee for Kaitlin Allison Arford Tasker
Certifies that this is the approved version of the following thesis:

Informing the Carbon Frontier:
Economics and Landscape in the Western Amazon

APPROVED BY
SUPERVISING COMMITTEE:

Supervisor:

Eugenio Y. Arima

Kenneth R. Young

Informing the Carbon Frontier:
Economics and Landscape in the Western Amazon

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Kaitlin Allison Arford Tasker, B.S.

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Abstract

Informing the Carbon Frontier: Economics and Landscape in the Western Amazon

Kaitlin Allison Arford Tasker, M.A.
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Supervisor: Eugenio Y. Arima

In recent years, forestry carbon offset projects have been on the rise. While praised for their ability to offset emissions inexpensively, these programs are also criticized for their tendency to overlook other important social, environmental and economic processes. This thesis examines the site of a major carbon offset program in the western Amazon of Peru as a case study for multi-objective conservation planning. Using a recently released high resolution carbon dataset, this study first identifies areas of highest above ground carbon density. It then innovates by generating models for two additional conservation measures: forest connectivity and deforestation probability. While the forest connectivity model is informed by landscape ecology and is a more simple modification of least cost path, the deforestation model uses principles of economic rent to produce spatially explicit probabilities.

By incorporating concepts of landscape ecology and economic rent, this work presents new models for the study area and adds to the theory surrounding multi-objective conservation planning. It also identifies if, how, and where three distinct

conservation criteria can find commonalities. Unsurprisingly, the three criteria result in distinct spatial patterns. When all three are prioritized, less than 3% of the study area qualifies for priority. However, while this analysis highlights the difficulty of simultaneously prioritizing all three criteria, it also offers hope. Landscape-level analyses can help policymakers and conservation practitioners prioritize these limited areas while household-level and broader contextual information can help inform how initiatives are ultimately implemented. Given the limited area under all three criteria, stakeholders can strengthen efforts by encouraging connectivity-enhancing land use practices, incorporating areas where two criteria are met, or further facilitating nearby community involvement. As pressures to marry social, environmental and economic continue, incentive schemes will need to rethink these strategies and innovate, and further research should be conducted.

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Chapter 1: Overview

This project uses the principles of landscape ecology and economic rent to inform current approaches for setting carbon conservation priorities. Reducing greenhouse gas emissions from deforestation and forest degradation is now a vital component in climate change mitigation strategies. Global initiatives such as the United Nations program for Reducing Emissions from Deforestation and forest Degradation (REDD+) are receiving increased investments (Ecosystem Marketplace 2014, Ecosystem Marketplace, 2011b)[1], and carbon offsetting has emerged in the form of both compliance schemes and voluntary markets (Bayon et al. 2012, Ecosystem Marketplace 2011a, Kollmuss et al.2008).

With over 247 carbon projects as of 2012, the country of Peru sits at the forefront of this carbon frontier.[2] Peruvian carbon projects draw an estimated investment of over US$12,800 million, and have experienced more than a one-thousand percent increase from the 18 projects in place in 2004 (FONAM 2012). As of 2013, Peru was the second-largest offsetter of carbon emissions worldwide (5.1 $MtCO^2e$)[3], with 14 afforestation/reforestation projects (Ecosystem Marketplace 2014).

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[1] In 2013, REDD comprised two-thirds of forest carbon offset transactions at the project level, with private sector buyers injecting millions of dollars towards halting tropical deforestation. Additionally, more than 80% of offsets were transacted from projects that reduce emissions from deforestation (REDD), with the majority sourced from Latin America—an area that tripled in activity since 2012 and to hold almost half of overall market shares in 2013.

[2] As of 2015, Peruvian carbon projects mostly fell under the umbrellas of Results-Based Financing (RBF), Reducing Emissions from Deforestation and Forest Degradation (REDD+), or more generally the private sector voluntary market (World Bank 2014). Results-Based Financing (RBF) describes funding approaches where payment is made upon delivery of verified pre-defined results (World Bank 2014) and is the financing approach where development objectives and policy goals feature most prominently. In contrast REDD+ projects can be national, jurisdictional or local in scale. Currently, the majority of REDD programs occur in the absence of a compliance mechanism, with funding from bilateral or multilateral sources (ex: Forest Carbon Partnership Facility). Nearly all REDD transactions are held on the voluntary carbon market (World Bank 2014), which in contrast to compliance markets (regulated by mandatory regional, national or international rules), allow companies and individuals to purchase carbon offsets as desired (Bayon et al. 2012, Kollmuss, Zink & Polycarp 2008).

[3] 5.1 million $MgCO^2$

However, while carbon projects have gained popularity among international investors and foreign aid programs, they are not without their critics. Policy interventions seeking to simultaneously reduce deforestation and poverty in tropical countries entail complex socioenvironmental trade-offs (Andersen et al. 2012). Despite their potential to reduce deforestation and increase the income of the poor (Andersen et al. 2012), carbon markets may also perpetuate harmful social and economic hierarchies (Lohmann 2009, 2012; Griffith 2008), misappropriate conservation resources (Andersen et al. 2012, Leguia, Malky & Ledezma 2011, Griffith 2008), and prioritize emissions avoidance over other forest characteristics that are important for conservation, such as tree-species diversity or habitat connectivity (Siikamäki & Newbold 2012, Strassburg et al. 2010, Putz and Redford 2009, Kirby & Potvin 2007).

To address these concerns, this research uses two key frameworks—(a) principles of economic rent and (b) principles of landscape ecology—to inform the prioritization of areas for carbon conservation in the northwest buffer zone of Cordillera Azul National Park (PNCAZ), San Martin, Peru. This research compares three different allocation schemes and the resultant landscape configurations for electing conservation sites. These three schemes are built on the following priority criteria, respectively: (1) highest aboveground carbon storage, (2) landscape connectivity, and (3) deforestation probability. While the aboveground carbon stocks are based on a recent study (Asner et al. 2014), the landscape connectivity model employs a modification of least cost path, and the deforestation probability model is spatially explicit, employing both physical and social-economic variables. By comparing the different spatial patterns of these schemes, this research seeks to answer the question, can a priority configuration be designed that finds commonalities with all three criteria?

Specifically, this study seeks to address the following:

(1) How does deforestation probability, as based on social and economic variables, vary spatially across the study zone?

(2) What areas in the northwest PNCAZ buffer zone might be most important for maintaining landscape connectivity?

(3) How does above ground carbon vary spatially as a function of (a) economic variables such as access to markets, and (b) landscape connectivity?

(4) (How) Can these three criteria be used to improve the cost effectiveness and additionality of carbon conservation projects?

(5) If these three schemes do result in different landscape configurations, what are some of the possible larger ramifications?

Answering these questions will be vital to maximize the cost effectiveness and additionality (i.e. the benefits above and beyond business as usual; more on this later) of carbon conservation funds in the future. Between 1997 and 2011, global land use changes were conservatively estimated to have resulted in a loss of ecosystem services of between $4.3 and $20.2 trillion per year (Costanza et al. 2014). Furthermore, habitat fragmentation is predicted to amplify the impacts of climate change by limiting available pathways for species movement and increasing the distance species need to disperse in order to persist (Nuñez et al. 2013, Straudinger et al. 2012, Coristine & Kerr 2011). In the case of Cordillera Azul National Park, long-term conservation will depend largely on the preservation of this habitat connectivity and conservation corridors.

Additionally, as evidenced by Cordillera Azul's 2011-2016 Master Plan, the northwest corner of the park's buffer zone—where this research focuses—has the highest number of roads, the most community settlements within less than 2 km of the park, and is at the highest risk of land conversion (Gomez et al. 2013, CIMA 2012). Formal and informal land use and development in the area are the result of cultural, economic and infrastructural factors. Determining compensation costs for this landscape is a complex process, tightly linked to local knowledge of sub-regional product quality, roads or other accessibility factors, as well as the location of markets (i.e. main locations for the sale of agricultural and non-agricultural goods).

By conducting research on economic and ecological landscapes, this work will provide new information for setting carbon market priorities. Voluntary carbon markets are still relatively new and little empirical research has examined the impacts of these programs—which could include habitat fragmentation, the displacement of local people, and the reinforcement of harmful social and economic hierarchies. Additionally, by incorporating new metrics for both deforestation and landscape connectivity, this research will contribute to a deeper, more complete understanding of deforestation and the market efforts to counteract it worldwide. Even if all three criteria cannot be optimized simultaneously, this effort provides insights into how the criteria can be used together to create an efficient allocation scheme (i.e. to obtain the biggest forest conservation and additionality per dollar) as well as insight into the larger social and ecological implications of carbon programs.

Chapter 2: Study Site

CORDILLERA AZUL NATIONAL PARK

This research focuses on the buffer zone of Cordillera Azul National Park (PNCAZ) in northeastern Peru (see Figure 1) and has been conducted in cooperation with the Peruvian Non-Governmental Organization CIMA Cordillera Azul (the Center for Conservation, Research, and Management of Natural Areas/*Centro de Conservación, Investigación, y Manejo de Áreas Naturales*).

Formed in 2002, PNCAZ encompasses 1.3 million hectares, and includes parts of four Peruvian departments—San Martin, Loreto, Ucayali, and Huánuco. It is home to hundreds of endemic species, including several that have been classified as new to science.[4] Its 2.5 million hectare buffer zone is meant to offer sustainable economic alternatives for more than 250,000 people in 400 communities (Althelia 2015, CIMA 2012, 2013).[5]

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[4] According to the Rapid Biological Inventory, conducted over three weeks in summer 2000, the northern Cordillera Azul region may have the highest concentration of habitat types among all Peruvian protected areas within the altitudinal range. The RBI team registered species of restricted range and habitat distributions for all organism groups sampled. In total, 1600 species of plants were registered (4,000 – 6,000 estimated for the region) including 12 species that were new to science. Additionally, the team registered 71 species of mammal (1 possibly new to science), over 500 species of birds (1 newly described, 3 new records for Peru), 82 species of amphibians and reptiles (9 potential new species), and at least 22 fish species that were new records for Peru, as well as 10 that were possibly new to science. In addition, many of these species are listed on CITES-I, and are considered endangered or critically threatened.

[5] According to the Cordillera Azul project overview provided by Althelia, these communities have "almost no economy apart from subsistence agriculture" and experience "a poverty rate of over 40%, or about the double of Peru poverty rater". Through the collaboration between CIMA Cordillera Azul, SERNANP and Althelia Climate Fund, the carbon financing is meant to provide funds to enhance "governenace of communities" as well as prioritize "the restoration of degraded lands in the buffer zone" by providing support for "sustainable agroforestry systems that combine food crops to enhance food security (i.e. banana, cassava), with sustainable cash crops such as cocoa and coffee to support poverty reduction, in partnership with local farmers cooperatives" (among other goals) (See https://althelia.com/investment/cordillera-azul-national-park-redd-project/ for details).

Upon the park's formation, CIMA Cordillera Azul signed an agreement with the Peruvian government to support the management of the park. In 2008, this contract was renewed through 2028 (IGES 2014) and CIMA began working to establish a forest carbon offset program in the PNCAZ buffer zone.

This first program was validated in 2012 under two international carbon standards—the Verified Carbon Standard (VCS) and the Climate, Community, and Biodiversity Standards (CCBS) (IGES 2014, SCSGS 2013, CIMA 2012). As part of the verification process, a historical deforestation rate was calculated and a dynamic analysis model was used to determine the business as usual scenario, useful for future evaluations of the mitigation effect of the park.[6]

However, while CIMA's carbon project was originally designed under the REDD framework (later transitioned to REDD+), in 2014 CIMA's program became part of a public-private partnership in collaboration with the Peruvian State (through the National Service of Protected Areas-SERNANP) and the Althelia Climate Fund (Althelia 2015). Through this public-private partnership, CIMA Cordillera Azul was awarded the highest number of carbon bonds to date at the recent twentieth Conference of the Parties for the United Nations Framework Convention on Climate Change (COP20) in Lima, December 2014 (MINAM 2014). The award of €8.55 million euros (approx. US $9.27 million) will be distributed over six years and is meant to help support CIMA's work in the buffer zone of Cordillera Azul National Park, including enhanced surveillance, biological monitoring, research, institutional strengthening, as well as the development of sustainable economic activities (Althelia 2015). These economic activities are said to prioritize the recovery and restoration of over 5,000 hectares of degraded lands, which

[6] The dynamic analysis used a regression model to derive the relationship between change in deforested area and change in population for the historical reference period (in this case, 1989-2003) and included information on distance to roads, rivers, towns, forest edge, and any indigenous areas, as well as data on elevation, slope, soil, vegetation, and geology as factors (SCSGS 2013, CIMA 2012).

the project currently estimates will offset 15 million tons of carbon dioxide emissions over the next six years. Additionally, the project outlines that CIMA plans to recover all of these hectares with the help of local small-scale farmers, who will "harness the agroforestry cash crops of coffee and cacao for a more sustainable future" (Althelia 2015).

While the buffer zone of PNCAZ lies across four departments, a main focus of CIMA's efforts is the northwestern-most section of the buffer zone, in San Martin. Given that San Martin is the most agriculturally productive department and the one experiencing the highest deforestation risk (Gomez et al. 2013, CIMA 2012), this thesis focuses on the same area (red box in Figure 1, Area of Interest in Figure 4). As of CIMA's 2008 census, the majority of settlers and newly arrived migrants were living within this zone, in the region known as the Huallaga Valley (Figure 1). At the time, the total number of communities in the Huallaga Valley section of the buffer zone was estimated at 181, with approximately 123,200 residents (an estimated 72% of the total residents for the buffer zone area) (CIMA 2012). Additionally, park guard workshops and geospatial analysis for the 2011-2016 Master Plan for Cordillera Azul National Park[7] clearly indicate that this section of the buffer zone has the highest number of roads, the highest number of communities located less than 2 km from the park, and is at the highest risk for land conversion (CIMA 2012). Many of these pressures are assumed to be due to agriculturally driven in-migration from the Andes, coast, and other regions (IGES 2014, SCSGS 2013, CIMA 2012, see Appendix for further information on the history of San Martin).

[7] Available for download at **http://www.cima.org.pe/es/publicaciones**, as of July 3rd 2016.

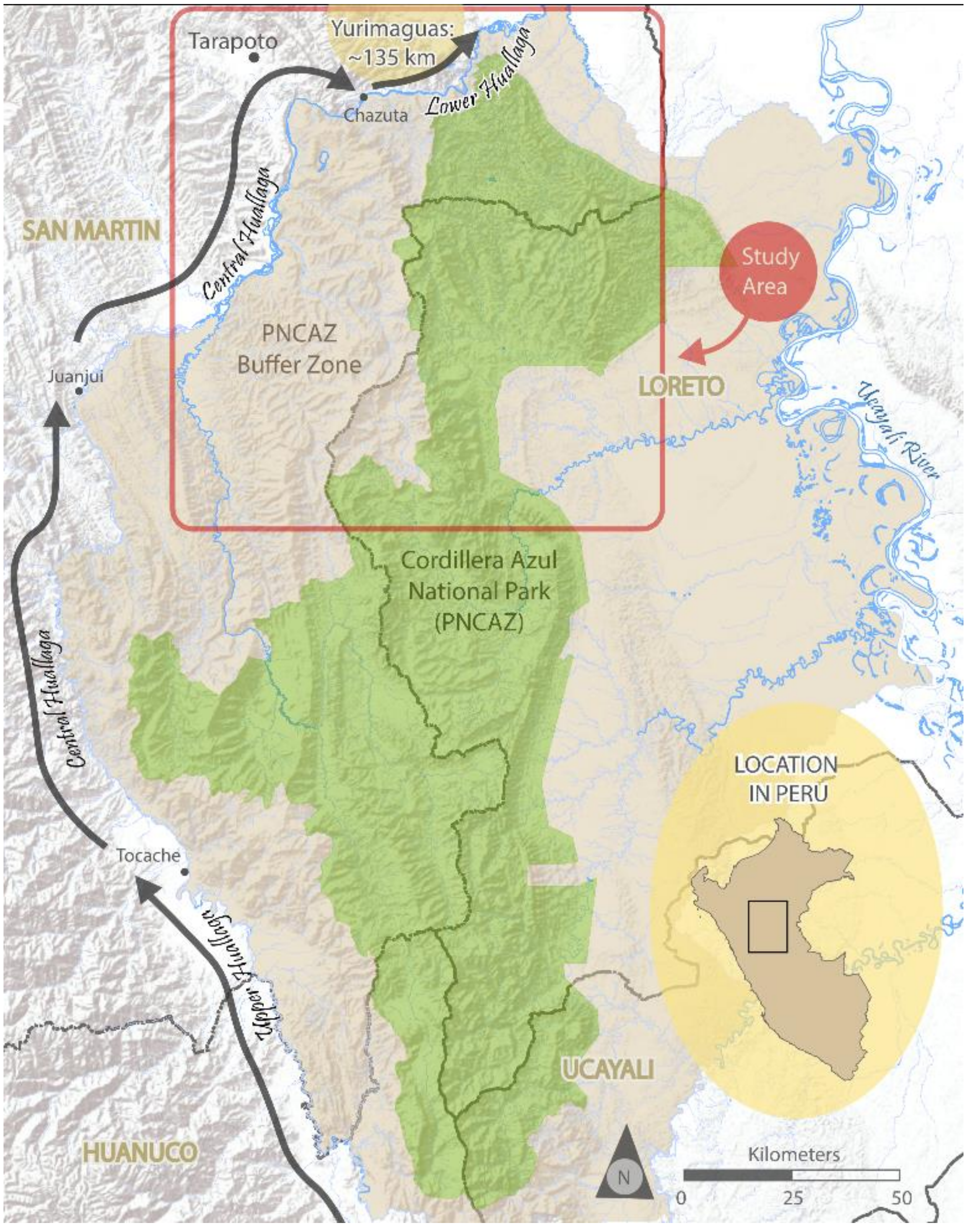

Figure 1: The Huallaga River valley.[8]

[8] A tributary of the Marañon, the Huallaga River stretches over 1,000 km (approx. 671 miles). While formal labels are limited, three informal designations have been widely adopted for the river's navigable section: upper Huallaga describes the source of the river in the Andes to the town of Tocache in San Martin, central Huallaga refers to the segment from Tocache up to Chazuta, and lower Huallaga describes the final segment from Chazuta to Yurimaguas (Ziesler & Ardizzone 1979).

Chapter 3: Conceptual Models & Analytical Framework

To determine whether carbon programs are innovating rather than just reinforcing the *status quo*, it is important to examine how conservation schemes based on aboveground carbon differ in spatial nature, extent, and cost effectiveness from schemes based on other factors—such as landscape connectivity or deforestation probability. Towards this end, this research uses a case study of the northwest corner of the Cordillera Azul National Park buffer zone in the Peruvian department of San Martin (the central Huallaga Valley) to compare the landscape configurations that result from three distinct schemes of assigning conservation priority. These three schemes are based on a) a high-resolution aboveground carbon density dataset provided by Greg Asner and colleagues (2014), b) a model of forest connectivity, and c) a model of deforestation probability.

Below, the analytical background for these schemes is presented to establish the main concepts and motivations behind the three models selected for comparison.

FOREST CARBON OFFSET PROJECTS

For decades, market-based mechanisms have been used as tools for environmental regulation and protection due to their efficiency (i.e. their ability to achieve the desired regulation cheaply).[9] This is due in part to the way that market mechanisms help internalize externalities, i.e. the costs or benefits that affect parties who did not choose to incur the cost or benefit.[10] By requiring the responsible party to repair the damage they

[9] While market mechanisms were first proposed as a tool for U.S. environmental regulation in the 1960s, the initiatives did not come to light until the US Acid Rain Program came into effect in 1990 (Lohmann 2009). This was followed by the establishment of a significant carbon trading instrument, the Kyoto Protocol, in 1997, and the joining of Europe to the carbon initiative by the early 2000s (Lohmann 2009). Since the early 2000s, investments in market mechanisms for conservation have been on the rise, with particular gains for carbon.

[10] For example: the air pollution costs one country experiences from an actively polluting neighbor.

have caused or to avoid it in the first place, market mechanisms effectively place the costs, benefits, and accountability back on to the original party.

In terms of carbon emissions and offsets, these mechanisms emerge in two forms: voluntary market trading or mandatory compliance (e.g. government regulated cap and trade programs) (Ecosystem Marketplace 2014, 2011a). However, while in the past carbon offsets may have been spread across the two, in recent years, the voluntary market has increasingly become the primary forum for forest carbon trading. As of 2010, it occupied approximately 42% of the total forest carbon trading market (Ecosystem Marketplace 2011a). Between 2012 and 2013 alone, the volume of offsets issued from projects that avoid deforestation, provide afforestation or reforestation, improve forest management, and incentivize sustainable agricultural practices tripled (Ecosystem Marketplace 2014).

For forest carbon offset programs initiated on the voluntary market, estimates are needed on the aboveground carbon density (ACD) that is present. For the purposes of this study, ACD information is sourced from a new high resolution carbon dataset (1 hectare resolution) made publicly available by Greg Asner and colleagues, and produced in cooperation with the Peruvian Ministry of Environment (Dirección General de Ordenamiento Territorial—Ministerio del Ambiente) and Wake Forest University (Asner et al. 2014). In the dataset, carbon is measured in megagrams of carbon per hectare (MgC ha^{-1}).

In addition to ACD, forest carbon offset projects (such as the on-going program in the buffer zone of Cordillera Azul National Park) require that certain criteria and verification standards be met. While levels and types of verification and validation may differ, additionality, leakage and permanence are the three most consistently required criteria today (Table 1, below).

Term	Definition
Additionality	The reductions in carbon that would not have occurred if business-as-usual (i.e. the emissions trends *before* the project was put in place) were allowed to continue.
Leakage	An unanticipated increase in emissions *outside* a project's boundary (ex: this can happen when land users divert activities to nearby areas, ultimately causing the same amount of deforestation, degradation, and/or emissions in a different spatial distribution).
Permanence	The length of time that carbon will remain stored after being sequestered, or the guarantee that the investment will remain intact for a sufficient period into the future so as to ensure that the carbon offsets purchased by the buyer (i.e. the avoided emisssions) are achieved.

Sources: World Bank 2014, Van Oosterzee et al. 2012, Kollmuss et al. 2008.

Table 1: Definitions of additionality, leakage, and permanence.

For the purposes of this study, the basic carbon model uses the new high-resolution dataset provided by Asner et al. (2014) to isolate those land parcels that represent the 80th percentile and above in terms of ACD. The model is later coupled with models for deforestation probability and forest connectivity for further analysis and discussion.

FOREST CONNECTIVITY

While forest carbon programs are generally expected to decrease rates of deforestation and forest degradation, measures of forest connectivity, biodiversity and future climate change vulnerability remain largely absent from these schemes. Defined as the degree to which a landscape facilitates or impedes movement among habitat and resource patches, landscape connectivity is an essential part of maintaining healthy ecosystems (Taylor et al. 1993, Merriam 1991, Baudry & Schreiber 1988, Merriam 1984). In its absence, forests may experience increased edge effects (i.e. more pronounced boundaries between habitats), changes in community structure, and inhibited movement.[11] On a local scale, this may affect wildlife's capacity to forage, predate or avoid predation, and to interact behaviorally. On a larger scale, it also determines their ability to migrate, maintain strong genetic diversity, and avoid a high incidence of infectious diseases and transmission (Satterfield et al. 2015, Nathan et al. 2008).

Landscape connectivity can be broadly organized into two categories—that of functional connectivity, i.e. processual connectivity between systems, and that of structural connectivity, i.e. the physical connectivity between habitats and populations (Doerr et al. 2014, Crooks 2006, Hilty & Merenlander 2006, Uezu et al. 2005, With et al. 1999). While functional connectivity deals with the actual degree to which dispersal and movement occur, and is of top importance for protecting ecosystems, gathering this data and determining system processes and functions can be quite difficult. Thus, in data sparse environments like the study site, structural connectivity is often used as a rough proxy for function (Calabrese & Fagan 2004). Defined as those physical links separating or uniting populations, landscapes and occupied habitats, structural connectivity takes a multitude of forms worldwide.[12]

This study specifies connectivity to links between forest patches of a certain size and uses a cost distance function alongside the concept of structural connectivity to calculate potential conservation corridor areas. While historic models of species movement under climate change have focused on the availability of species-specific habitat or on standard measures of connectivity (Spencer et al. 2010; Hunter et al. 1988; Noss 1987), recent models have begun incorporating assumptions on species movement as restricted by anthropogenic barriers (Nunez et al. 2013). Cost-distance modeling—a

[11] For more on this, see Insular Biogeography (also known as Island Biogeography), a field founded by ecologists Robert H. MacArthur and E.O. Wilson in the 1960s (MacArthur & Wilson 2015 is the newest adaptation of the 1967 original book).

[12] Examples of structural connectivity include drainages, overgrown fence lines, intact forest patches, and habitat corridors.

computationally efficient approach used to identify the relative importance of areas between patches for ecological movements (Adriaensen et al. 2003)—has often been used for this work, generally with success. Under such models, weights or friction values are assigned to each pixel and used to specify the given cost for crossing it (Beier et al. 2008; Adriaensen et al. 2003). The general formula for cost distance can be described as: Cost = (Cost of travel over a surface) * (Characteristics of the mover) * (Movement characteristics on the surface).

DEFORESTATION PROBABILITY

While in the past, CIMA Cordillera Azul established the business-as-usual calculation for deforestation within PNCAZ and its buffer zone through a linear regression between population growth (including in-migration) and annual hectares deforested (CIMA 2012), conditions have changed. Since the original calculation, CIMA program officials report that the rate of population growth has stayed relatively consistent while the rate of deforestation has begun to decline—likely due to either scarcity of land or increased productivity per hectare (field interviews, 2015).

This study examines deforestation at the landscape level and assumes that deforestation probability is driven by biophysical (e.g. elevation, slope, and soil type) as well as social (population) and economic variables (e.g. access to roads and markets and institutional factors). Under this model, landusers are assumed to be rational profit and/or utility maximizers, who are more likely to deforest a given area when rents from agricultural land uses (R^a) are greater than those obtained from standing forests (R^f) (Arima 2016, Nelson et al. 2001, Chomitz & Gray 1996). In turn, these profits, known as agricultural rents, are a function of transportation cost (for a further explanation of rent, bid-rent and their relationship to deforestation probability, see Appendix).

Given that rent is equal to the prices received for agricultural or forest products net of transportation costs minus production costs, this model employs freight cost as a proxy for economic rent. More specifically, rents for a given plot of land, *i*, depend on the prices of agricultural and forest products, minus the transportation costs involved with getting those products to market. As such, rents can be stated as a function of the distance and difficulty of transportation (Arima 2016, Nelson & Hellerstein 1997, Chomitz & Gray 1996). The likelihood of a given plot of land *i* being deforested is then modeled as a linear function of transportation costs alongside other control variables for biophysical and socioeconomic characteristics.

Unlike other forms of regression analysis, a logit regression is used to predict binary independent variables (in this case, that *y* is either equal to 1, deforested, or 0 otherwise). The probability of observing deforestation in cell *i* can thus be stated as:

$$\Pr(y_i = 1 \mid \mathbf{x}_i) = \frac{\exp(\mathbf{x}_i\boldsymbol{\beta})}{1 + \exp(\mathbf{x}_i\boldsymbol{\beta})}$$

Where x is the vector of explanatory variables and β is the vector of coefficients associated with the vector of controls. In similar fashion to the theory provided by von Thünen (1966)[13] and the adaptation provided by Chomitz & Gray (1996) (see Appendix), the explanatory variables include transportation costs (cost distance) to approximate rent,[14] the rate of change for nearby human populations (relative effect of population), and slope. The vector of controls includes elevation, precipitation, soil type and protected area status (Table 8).

Assuming that agents act to maximize profit, the probability of observing deforestation ($y = 1$) can be written as a formal logistic model as follows:

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[13] This represents the English translation of *Der isolierte Staat* (The Isolated State), originally published 1826.

[14] i.e. the analytical framework assumes that there is a value for rent attached to each use of each plot of land within the study area, and that this rent will ultimately impact what activity the land's use is devoted to

$$P(y^* > 0 \,|\, \mathbf{x}_i = P(\, e > \frac{1}{1+\exp(\mathbf{x}_i\boldsymbol{\beta})} \,|\, \mathbf{x}_i = \mathrm{f}(\mathbf{x}_i\boldsymbol{\beta})$$

$$y_i = \begin{cases} 0, & \text{if } y^* < 0 \\ 1, & \text{if } y^* > 0 \end{cases} \begin{cases} 0, & \text{if } y^* < 0 \\ 1, & \text{if } y^* > 0 \end{cases}$$

where f is the logit.

In this study, economic rent is assumed to correlate positively with the probability of deforestation. This is due to the fact that scarce factors of production—whether it be land location or quality—will ultimately determine the profitability and thus desirability of the land. Similarly, bid-rent ensures that this land, if profitable, will be brought into production for its most profitable use (see Appendix). While there are some cases where deforestation is expected to yield lower rent than an alternative activity,[15] these cases are generally rare and often the result of the land being poorly suited for agriculture, or an alternative development initiative being put in place. Figure 2, below, shows the relationship between deforestation and rent assumed by this study.

[15] For instance, if the economic rent derived from forestry is greater than that derived from agriculture, the forest may actually be harvested more sparingly and managed for long-term growth, rather than being cut.

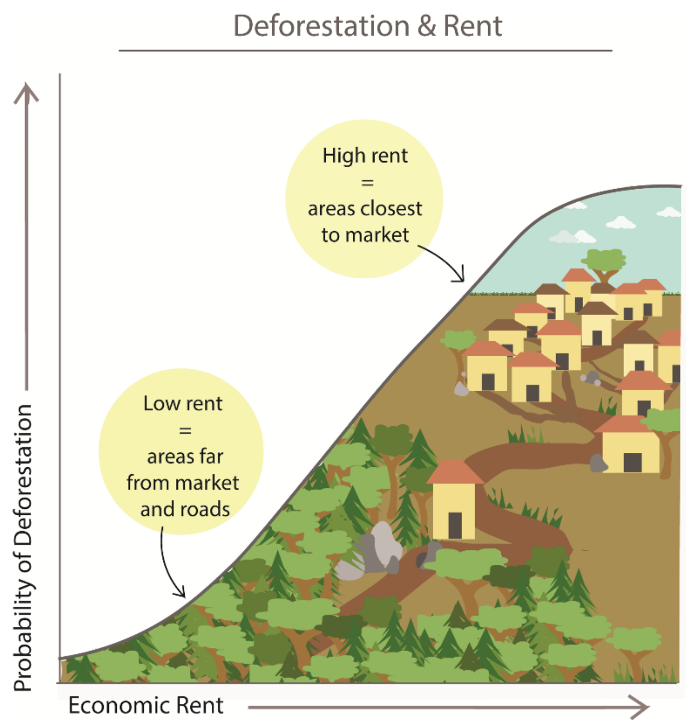

Figure 2: General relationship between economic rent and deforestation.

However, despite the assumed positive relationship between economic rent and deforestation probability, not all sites are equally cost effective for conservation. Instead, one must also examine the opportunity cost of intact forest (Plumb et al. 2012, Fisher et al. 2011, Naidoo and Adamowicz 2006). Figure 3 divides the relationship between economic rent and deforestation into three sub-categories. The lands on the right are those with high profitability and at the highest risk for deforestation. These lands are likely to experience high opportunity costs and thus require a higher financial offer to bring the land out of production. In contrast, the lands on the left represent those with low profitability and are at a lower risk for deforestation. While these may be less costly to bring out of production, a conservation NGO or institutional body would be hard pressed to prove that the land was under risk of deforestation and thereby eligible for "offset" programs.

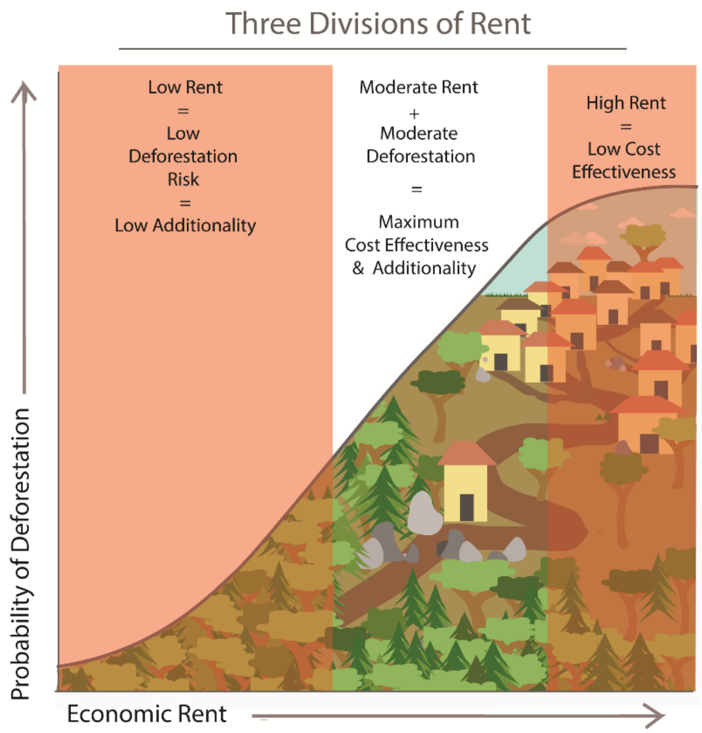

Figure 3: The three major divisions of economic rent.

Given these divisions, the deforestation model employed by this study focuses on the central category—where rent and deforestation probability are neither the lowest nor highest. In contrast to the lands on the left and right, these central areas *do* experience moderate levels of deforestation—and are thus good candidates for additionality—while also being employed for activities of *moderate* rent. This means there is a good chance that conservationists could afford to compensate landowners at or above their current rent values, to offset the deforestation-generating activities.

Chapter 4: Methods

As described earlier, this thesis seeks to compare three schemes for assigning conservation priority as based on (1) highest aboveground carbon stocks, (2) deforestation probability, and (3) landscape connectivity. Given that the first scheme (carbon) relies on a pre-existing dataset produced by Asner et al. (2014), methods for this model have been separated out. First, a brief overview of Asner et al.'s (2014) methods are presented. This is then followed by a section describing the model variables and data sources used for landscape connectivity and deforestation probability, as well as a final explanation of how these variables were employed.

CARNEGIE AIRBORNE OBSERVATORY'S HIGH-RESOLUTION CARBON MAP

The new carbon dataset provided by Asner et al. (2014) uses available satellite and geographic information systems, airborne Light Detection and Ranging (LiDAR), and field plot calibration data to develop maps of aboveground carbon density (ACD) as well as spatially explicit estimates of uncertainty. For the purposes of this study, this data was largely used in its original form (minor modifications may have occurred during calculations).

To produce the model, Asner and colleagues (2014) combined maps detailing the country's geology, soil, floristic communities, elevation and forest cover. These maps were used to forecast the potential environments and conditions that could be encountered during the airborne surveys that were to follow. The authors then divided the country of Peru into 200 x 200 km sampling pixels, and used airborne LiDAR to sample extensively.[16] To ensure that more than sufficient sampling had occurred, the methodology covered large areas of each potential set of environmental conditions (determined previously). Following airborne LiDAR surveys, the authors also combined a "diverse array" of satellite data in order to provide "continuous geographic information on vegetation cover, topographic variables and climate" (Asner et al. 2014). Both the satellite data and LiDAR were processed through geostatistical modelling. They were then combined with calibrations of LiDAR to field-estimated carbon stocks. The ultimate result was spatially explicit maps of both aboveground carbon stock estimates and uncertainty.

For the dataset, carbon is measured in megagrams of carbon per hectare (Mg C ha−1). Nation-wide carbon density measurements range from <0.01 to 156.89 Mg C ha^{-1} with an average of 0.31 Mg C ha^{-1} (uncertainty ranges from <0.01 to 34.66 Mg C ha^{-1}). Within the study site, density is slightly higher, with an average density of 67 Mg C ha^{-1} (ranging from 0.11 to 150.09 Mg C ha^{-1}).

LANDSCAPE CONNECTIVITY & DEFORESTATION PROBABILITY TECHNICAL MODELS

Data Sources

In addition to Asner and colleagues' (2014) carbon data, this study employs two other models, generated a combination of field work, publicly available data, and geospatial processing. Field work for this project was conducted in San Martin, Peru from June 17th to August 4th, 2015 and focused on three main components: (1) interviews with local farmers, (2) interviews with agricultural and conservation professionals in the

[16] In the case of this study, "airborne LiDAR" refers to a twin turbopropeller Dornier 228 aircraft, carrying the Carnegie Observatory-2 Airborne Taxonomic Mapping System (AToMS; Asner et al. 2012). The AToMS LiDAR is described as "a dual laser, scanning waveform capable of firing at 500,000 laser shots per second".

area, and (3) GPS ground verification of remotely sensed and other digital format data[17] (see Table 2).

Component	Specific Goals	Accomplished
1) Interviews with local farmers and land users within the buffer zone	A) Collect records of freight cost from farmgate to market and identify main transportation routes and destinations B) Identify perceived drivers of deforestation, as well as underlying conditions that may affect land use C) Collect a contextual history on land use and migration in the area	• Interviews and focus groups in 6 communities, with 36 individuals
2) Interviews with agricultural, conservation or forestry professionals (including truck drivers and intermediaries)	A) Confirm or add new perspective to information gained through farmer interviews B) Construct an agricultural history of the area C) Identify key programs and actors currently or previously active in the agricultural or conservation sector in the area	• Interviews with 9 CIMA field technicians • Interview with Jose Santiesteban, *Dirreccion Regional de Agricultura*
3) Ground verification with GPS	A) Verify locations of roads, water bodies and communities B) Verify road condition	• Personally travelled over 90% of the study region • 100 GPS verification points collected

Table 2: Three main components of field work and associated goals.

The semi-structured interviews used in component 1 and 2 of this study were designed to glean information on freight costs. Interviewees were identified via snowball sampling, with study subjects helping recruit future subjects among their acquaintances and/or within the same community or institution. In the case of farmers (component 1), these interviews consisted of 26 questions designed to gather information on farmer

[17] Ground verification involves the collection of a set of measurements (usually at the real, physical location) that are known to be more accurate than the set of measurements used in the system you are testing. By collecting this second set of measurements, large-scale (large??) data can be verified and calibrated to better approximate real locations or conditions.

migration patterns, preferred crops, profit and cost associated with cultivation, as well as temporal and spatial variability in access to markets (see Appendix). Interviewees were also asked about the routes they use to transport their products throughout the year and the freight costs associated with transport. While many of these responses were ultimately used contextually, spatial and temporal information on freight cost was used for the deforestation probability model in this study (see Tables 6 and 7). Of the 36 semi-structured interviews conducted with farmers, all identified proximity to market (specified as distance to roads or a main town) as one of the top two factors affecting land value (i.e. price). The second most consistently identified factor was water (present in approximately 75% of interviews), followed by slope (about 25%).

Interviews for component 2 were similar to farmer interviews, but can best be understood when broken into three types: interviews with CIMA field technicians and staff, interviews with other regional or government agricultural authorities, and interviews with truck drivers. For the first category, interviews were conducted with all 9 field technicians working within the area of interest (AOI).[18] For this study, each field technician was asked the same generalized set of 26 questions as farmers, modified for their work region. How long they had worked in the area and where they worked previously were also recorded. Finally, each field technician was asked to sketch maps of the region where they work, identifying the main crops, communities, pathways of transport, and costs of transport throughout.

Both farmers and field technicians were asked to identify the location of main market centers and intermediaries where their products are sold. In total, interviews of farmers and CIMA field staff resulted in 115 records for total freight cost between two

[18] CIMA field technicians work with approximately 3 to 5 communities in the buffer zone of Cordillera Azul National Park, with aims of establishing community norms for co-living, establishing goals for the community's social, economic and environmental future, and providing technical or administrative support in achieving these goals.

points (81 were unique, more on this later). Records for freight cost to a given market were converted to soles per km per sack of product (one sack = 60-65 kilos) by dividing the total reported freight by the distance from the community to market in a GIS. Interviews also yielded information on local product prices, knowledge of sub-regional product quality, and transport preferences.

In addition to these main groups, 6 other interviews were conducted; 3 with agricultural professionals in the area and 3 with truck drivers along the main product-transport routes. Interviews with agricultural professionals were much more open ended and sought to identify the history of land use in the area, the agricultural support services currently being offered, and new initiatives that were underway as a part of the popular 'alternative development' movement in the area. In contrast, interviews with truck drivers focused on identifying main routes, common stops, main products transported, and the prices charged across the zone. While only three interviews were conducted, information from truck drivers largely confirmed the freight cost data provided by farmers. Additionally, all three drivers covered different spatial domains within the study area.

In terms of digital data, all files were either originally in or converted to raster format, projected to the UTM coordinate system and then resampled to 100 m resolution using nearest neighbor algorithms. This cell resolution was selected as it represented a good compromise among the different resolutions for available data. The area of interest (AOI) was then defined by masking out areas of open water,[19] and areas within Cordillera Azul National Park boundaries. Given that this area is under specific protection, including park data could skew results if institutional factors are not accounted for. The remaining 100 m cells are the units of observation (n = 481,622) and include approximately 4,817 ha of terrestrial area (Figure 4).[20]

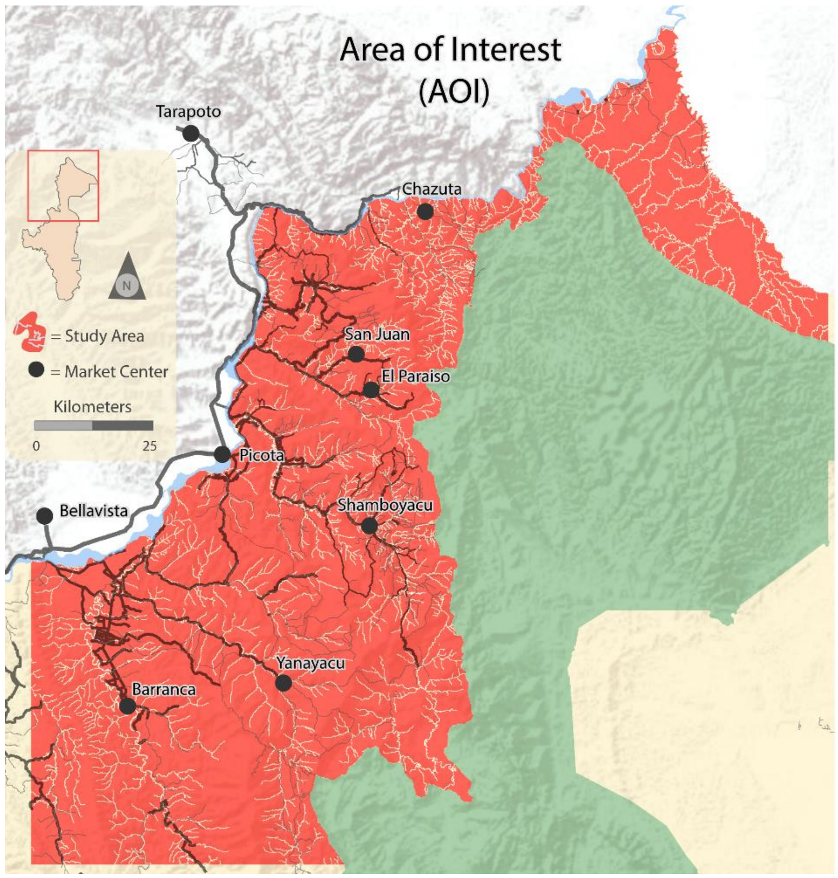

Figure 4: The area of interest (AOI).

Both the landscape (forest) connectivity and deforestation probability models employ several social, economic, and biophysical variables. Below, each of these variables is briefly outlined. At the end of the section, Figure 5 displays the spatial nature of these variables through a series of maps. A basic schematic then follows indicating how each variable was utilized (Figure 6).

[20] The AOI excludes water bodies, 4,275 ha of national park land, and 6,424 ha of land outside both the park and buffer zone boundaries.

Model Variables

Forest Cover

Forest cover is a binary variable (1 = deforested, 0 = forested) that forms the dependent variable in the deforestation probability model. Deforestation was identified using the Global Forest Change 2000-2013 data published by Hansen et al. (2013). This dataset was originally available at a resolution of 30 meters, and provides information on tree canopy cover in the year 2000 as well as forest loss (2000-2014), forest gain (2000-2012), year of forest loss (annual basis, 2001-2014) and a data mask showing areas of no data, mapped land surface and permanent water bodies. To create the binary forest/no-forest raster, tree canopy cover in 2000 was used as a base, then adjusted using GIS operations to account for both gains and losses from 2000-2013.

Over the past two decades, deforestation in the study area has largely correlated with road development. Shamboyacu was one of the first major market centers established, and in the early years deforestation followed the road down from Picota towards this epicenter, before branching off to form a dendritic pattern of deforestation and dirt (*trocha*) roadways towards the communities of Santa Rosa, Lejia, Nuevo Amazonas, Vista Alegre, and onto Alto Ponasa. Recent years have shown a similar pattern appearing farther south. As more and more migrants from neighboring regions move in to the area, roads have been created from Bellavista, which lies outside the buffer zone, into the interior. Following this trajectory, the towns of Nuevo Lima, Nuevo Tarapoto, Yanayacu and finally San Juan have developed. While still largely a frontier town, San Juan has also given way to additional expansion even closer to the park's boundary. Interviews conducted in the summer of 2015 revealed that in the case of these communities, most inhabitants have come from Cajamarca, a town in the Sierra region. Many of them also confirmed that they had been sold lands in the area (likely illegally), which they had then relocated to claim (more on this in Chapter 6: Discussion). Because of this expansion approximately 22.5% of the AOI was deforested (1,106.74 ha) in 2013 (Table 4, Figure 5). While 77.5% remained forested (3,734.69 ha), these areas face increased pressure as expansion continues.

Roads and Waterways

As discussed in previous sections, transportation costs are known to affect both the price of inputs and the prices of agricultural products, which in turn impact land rent. To account for these costs, line, point, and polygon vector GIS files indicating the locations of roads, water bodies, communities, and park and buffer zone extent were provided by CIMA Cordillera Azul. In the case of roads, the data provided by CIMA indicated the type of road, with categories of Asfaltado (Asphalt), Afirmado (Reinforced), Sin Afirmar (Un-Reinforced), and Trocha (Dirt pathway or trail). In the case of waterways, each river or stream was classified not only by a categorical marker (river, stream, etc.) but also by a class value. To verify the accuracy of these datasets, 100 GPS points were taken along transport routes during the field work conducted for this research. Road condition was noted, as were the communities, market centers, and main crops along the way. Once verified, CIMA's GIS files were converted to individual rasters using simple GIS operations for value isolation and feature-to-raster conversion.

For the deforestation probability models, three variables were generated using this data. The first is cost distance (explained in further detail in the section to come). In the AOI, cost distance has a minimum value of 0, a maximum value of 14.48 and a mean value of 3.19. In addition, two variables for Euclidean distance from road and waterways, respectively, were also created. While these variables were never used in concert with cost distance, they were used as a proxy in the second deforestation probability regression. For the AOI, Euclidean distance to roads (EDroads) has a mean value of

2,355.55 while Euclidean distance to water (EDwater) has a mean equal to 636.39 (Table 4).

Relative Effect of Population (REP)

CIMA's work in the buffer zone of Cordillera Azul National Park included surveys of the communities they work with in the area. These surveys (called MUF, the Mapping of Uses and Benefits, i.e. "Mapeo de Usos y Fortalezas") have taken place approximately every 2-3 years since 2003 (2003, 2005, 2008, 2012) and include information on the number of people, dwellings and families in each community visited, as well as general sentiments about the park, community relationships, goals, and origins (MUF 2003, 2005, 2008).

Given that both the size of adjacent populations and the distance from a given population are thought to relate to deforestation probability (Geist & Lambin 2002, Turner et al. 2001, Wibowo & Byron 1999, Mather et al. 1998, Vanclay 1993, Myers 1991, Allen & Barnes 1985), a scale variable was calculated to indicate these two factors simultaneously. Labeled the "Relative Effect of Population" (REP), this variable is similar to Gravity Models[21] in that it gives each pixel *i* a value equal to the change in population of the closest community divided by the Euclidean distance from that community, as follows:

$$REP_i = \frac{(Pop_{2008,m} - Pop_{2005,m})}{ED_{i \rightarrow m}}$$

Where *i* is a given plot of land, *m* is the closest reported community to plot *i*, Pop_{2008} *and* Pop_{2005} are the population in community *m* in years 2008 and 2005 respectively, and $ED_{i \rightarrow m}$ is the Euclidean distance from plot *i* to the nearest community *m* in km as reported in a GIS.

[21] See Anderson 2010 for more on this topic.

While data from 2003 was available for some communities, many of the communities in the study area were either not yet established or else not included in the survey that year. In 2005, population data was available for 141 communities, with a maximum population of 1500 and a minimum population of 0 (mean = 119.58; std. dev. = 222.68). Three years later, the number of communities reported remained the same. Though the maximum population had decreased to 1200, both the mean population (mean = 293) and standard deviation (std. dev. = 282.50) had increased. Euclidean distance was then calculated from each pixel to the nearest community in a GIS. Euclidean distance for each pixel within the study area ranged from a minimum of 0 meters (at the population) to a maximum of 51,127 meters (mean = 29,154 meters).[22] Ultimately this resulted in *REP* values ranging from -11.21 to 10.19, with positive values indicating areas where the population has increased during the time period (Table 4, Figure 5).

Soil Type

Data on soil type was retrieved from International Soil Reference and Information Center (ISRIC) using the SoilGrids 1km collection. This dataset provides a categorical classification for each pixel, from among 32 different soil groups. In the case of our study area, 12 distinct groups are present and occupy anywhere from less than 1% of the study area to over 45% (see Table 3, below).

[22] I.e. a given pixel 100 km from a community with population increase of 500 individuals, and a pixel 200 km from a community with population increase of 1,000 individuals have the same value.

Soil Group	% AOI
Acrisols	45.7%
Ferralsols	27.0%
Kastanozems	17.3%
Solonchaks	2.7%
Luvisols	2.2%
Gleysols	1.5%
Cambisols	1.2%
Leptosols	1.4%
Histosols	<1%
Nitisols	<1%
Umbrisols	<1%
Vertisols	<1%

Table 3: Soil types found in the study area.

While this data is the product of an automated global soil mapping system, and may contain some spatial or thematic inaccuracies, artefacts and/or missing pixels, it was selected for two main reasons. First, soil is an important component in both road establishment and agriculture. As such, it is key to account for variations in soil when examining deforestation probability. Second, there is limited soil data available for the study area and this dataset provides one of the higher resolution options, with no missing pixels for the given study site.

Elevation and Slope

The Digital Elevation Model (DEM) used in this study was obtained from the Peruvian Ministry of the Environment's Geo Server (geoservidor.minam.gov.pe) and is a product of collaboration between the Japanese Ministry of Economy, Trade and Industry (METI) and NASA. Data resolution is 30 meters; the result of 1.3 million images from the ASTER high resolution imaging instrument on the Terra Satellite. To create the Elevation variable, four DEM tiles were selected and mosaicked together using GIS operations (S07W077, S07W076, S08W077 and S08W076).

Elevation in the AOI ranges from 120 m.s.l to 2,992 m.s.l., with an average elevation of 554.06 meters (Table 4). Slope was calculated by performing pre-existing ArcGIS® operations on the mosaicked DEM tiles and is presented in degrees. For the AOI, slope ranges from 0 to 82.98 degrees with a mean slope of 9.37 (Table 4).

Precipitation (TRMM)

Precipitation was calculated using Tropical Rainfall Measuring Mission (TRMM) product 3B43 Version 7. TRMM reports monthly precipitation in mm/hr and combines the estimates generated by the TRMM satellite sensors, other satellite products, and CAMS global gridded rain gauge data. While this mission ended on April 15, 2015, it provided 17 years of scientific data and ultimately became the space standard for measuring precipitation. For this study, TRMM data for 2000-2013 were converted to mm/year and then averaged to get the mean mm/year for each pixel during the time period. For the AOI, average TRMM for this period ranges from approximately 1,397 to 2,186 mm/year (mean = 1,668 mm/year) (Table 4).

Variable	Min	Max	Mean	Std. Dev.	Type of Data
Forest Cover	0.00	1.00	0.78	0.39	Binary
EDroads	0.00	31,549.60	2,355.55	0.46	Continuous
EDwater	100.00	4,204.76	636.39	2.34	Continuous
Cost Distance	0.00	14.48	3.19	1.83	Continuous
Relative Effect of Population (REP)	-11.21	10.19	$1.90E^{-3}$	$4.07E^{-4}$	Continuous
Slope	0.00	82.98	9.37	0.18	Continuous
Elevation	120.00	2,992.00	554.06	0.23	Continuous
Soil Type	N/A (See Table 3)				Binary
TRMM	1,397.75	2,186.79	1,668.92	230.79	Continuous

Table 4: Descriptive statistics for variables in the AOI.

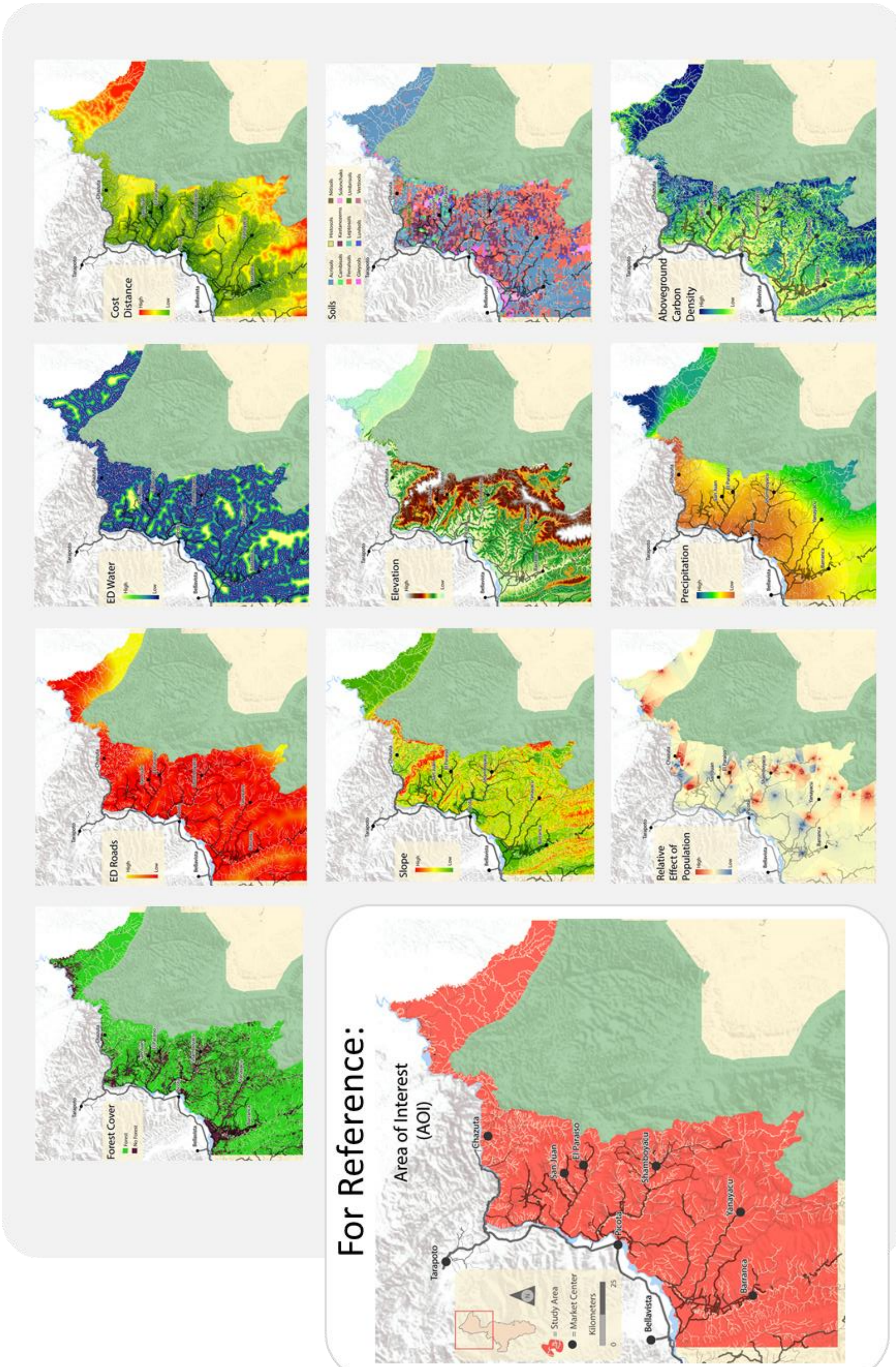

Figure 5: Maps of the key variables within the AOI.

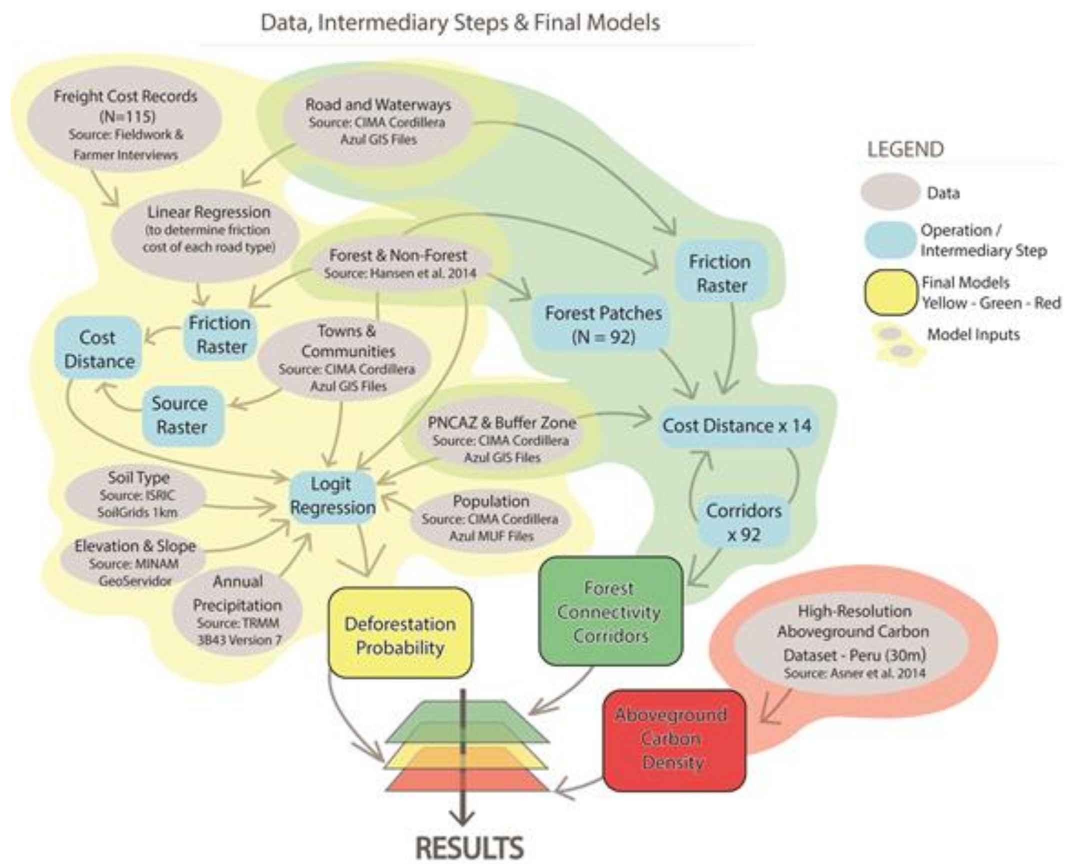

Figure 6: Data components and modelling process.

Landscape Connectivity

Determining Forest Patches

For the forest connectivity model, intact forest patches were identified using the Hansen et al. 2013 dataset informed by some ground verification by CIMA Cordillera Azul employees. The dataset was used to identify forested and deforested areas as well as areas of bare land[23], and where data was unavailable.

[23] Bare land can be differentiated from deforested land by the fact that bare land is consistently and naturally bare.

For the purposes of this study, forest patches encompassing at least 1,000 hectares of forest and found in the buffer zone of PNCAZ were selected and isolated in individual raster files of equal spatial extent (i.e. each raster file isolated a single forest patch). In total, 14 patches were created, with patch sizes ranging from 1,104 to 491,324 hectares and a mean patch area of 97,255 hectares.

Determining Friction & Calculating Cost Distance

Models for landscape connectivity (in this case, forest connectivity) often involve a modification of cost distance and least cost path, using friction as the cost source. For the purposes of this study, friction was calculated on a scale of 1-20 for each pixel within the study area. Pixels representing asphalt and market centers were assigned a value 20 times more costly than those representing intact forest patches (as based on Arima et al. 2007), with all other areas placed along the spectrum between the two (Table 5).

Description	**Friction**
Asphalt road	20
Market Centers	20
Huallaga	18
Areas within 0.5 km of asphalt road	18
Other communities	16
Areas within 0.5-1 km of asphalt road	16
Reinforced roads (*afirmado)*	14
Areas within 0.5 km of reinforced road (*afirmado)*	12
Areas within 0.5-1 km of reinforced road (*afirmado)*	10
Unreinforced road (*sin afirmar*)	10
Areas within 0.5 km of unreinforced road (*sin afirmar*)	8
Dirt roads (*trocha*)	6
Unforested/Deforested	6
Small rivers	6
Areas within 0.5 km of dirt roads (*trocha*) or deforested areas	2
Intact forest patches	1

Table 5: Friction values for the forest connectivity model.

Corridor Model

Once friction costs were established, a cost distance function was run 14 times—each using the friction raster as the basis for the cost and a unique forest patch raster as the origin or source. To create corridors, the results from two of these cost distance functions were selected (i.e. cost distance for a pair of forest patches) and the values for each pixel in both rasters were summed. This resulted in a new raster indicating the cumulative cost, in both directions, between the two patches for any given pixel. In total, 91 unique forest patch pair corridors were generated within the AOI with average cumulative corridor costs of 40,272 per 100-meter pixel (min = 100; max = 150,033).

The 91 cumulative cost rasters were separated into quantiles of equal area using GIS operations. These operations were performed twice—once to yield a map of the lowest one percent of cost pixels (100 quantiles) and once to yield a map of the lowest five percent of cost pixels (20 quantiles). These lowest cost corridors were then joined into single binary rasters, respectively, where a value of 1 indicates the pixel is included in at least one least-cost corridor and a value of 0 indicates that it is not. This methodology was selected because it maintains equal weight for each corridor, regardless of corridor distance, patch size, or cost differences for crossing between different patch pairs, while also maintaining a reasonable level of scrutiny (i.e. a reasonable sample size).

Deforestation Probability

To ensure that the proxy for economic rent (i.e. freight cost) is robust, two separate methods were used and compared. The first accounts for the distance that a given plot of land lays from roads and waterways (also used for transport) through simple Euclidean distance calculations. The second uses field data and spatial analysis to identify land and infrastructure classifications and assign them unique friction values, which are then used to calculate a given plot's cost distance to market. These two methods attempt to account for the same effect and thus were never used in combination. Results from both are compared in the following chapter (Table 9). A more thorough explanation of the methods for calculating cost distance is given below.

Calculating Cost Distance

Calculating cost distance requires both a friction raster—indicating the relative difficulty of crossing each pixel within the study area—as well as a source raster—the pixels (locations) to which the least accumulated cost distance is calculated. For this study, the friction raster was created using road condition and water bodies (CIMA), forest and non-forest areas (Hansen et al. 2013) and data on freight cost (field work, summer 2015; see left panel, Figure 7). The source raster used market centers as the source pixels of interest (red dots in Figure 7).

To determine a relationship between road condition, distance and cost, information from field interviews was processed into records of freight cost. Given that these records were obtained through interviews, most involved transit from a given community to a point of sale—typically a larger community or market center—rather than travel along a particular isolated section of road. Because of this, the records often involve multiple kinds of road condition and may also be repeated in various interviews with various community members. To determine unique records, each instance of reported freight cost was recorded in terms of the start and end point of the journey, as well as any important deviations that were noted (e.g. if there are two routes between the start and end point, the interviewee indicated which route they were discussing). To eliminate repeat observations of the same route and cost, only one record of this route was utilized in the linear regression that followed. This processing revealed 81 unique records of freight cost.

The unique records of freight cost were processed alongside data on distance obtained from a GIS to determine approximately how many kilometers of road along the travelled route were asphalted (*asfaltado)*, reinforced (*afirmado)*, without reinforcement (*sin afirmar)*, and dirt (*trocha)* respectively. A linear regression was then performed using total freight cost for the segment (soles/sack/km) as the dependent variable, and employing the four road categories as independent variables, as follows:

$$y_i = \boldsymbol{\beta_1} Asfaltado + \boldsymbol{\beta_2} Afirmado + \boldsymbol{\beta_3} Sin\,Afirmar + \boldsymbol{\beta_4} Trocha + \varepsilon_i$$

Linear regression results were significant for all road types except asphalt (p-value = 0.17) and indicated a positive intercept coefficient as well. This coefficient indicates the fixed costs required to travel, regardless of distance. In this case, the intercept coefficient was equal to 7.84 soles per sack per kilometer (Table 6).

While units for the regression were soles per sack per *kilometer* (1 sack = 60-65 kilos; Table 6), these were converted to soles per sack per *meter* for the friction raster, to maintain consistency with the pixel resolution (100 sq. meters) (Table 7).

Road Type	**Coefficient (SE)**	***N***	**Unit**
Intercept	7.84 (1.77)***	81	Soles per sack per kilometer
Asphalt (*Asfaltado*)	0.0929 (0.06)		
Reinforced (*Afirmado*)	0.1247 (0.08)**		
Without Reinforcement (*Sin Afirmar*)	0.4990 (0.36)*		
Dirt (*Trocha*)	0.8788 (0.18)***		
*p<0.1, **p<0.05, ***p<0.001			

Table 6: Results from freight cost linear regression.

Once friction values were obtained for each road type, these values were applied to the road raster (i.e. each pixel designated as *trocha* was assigned the friction value for *trocha*, and so on). Forest and non-forested areas were also assigned friction costs, as were water features. For water features, friction values were based on a previous study using information from Wildlife Conservation Society in the nearby region of Loreto (Arima 2016). Those areas not designated as forest, road or water were given a friction value equal to "*trocha*". Forested pixels were given a friction value 20 times higher, as according to previous work (see Pinto & Keitt 2009 and Arima et al. 2007) (Table 7). Once the friction and source rasters were complete, they were used to run a cost-distance model from each pixel to the source pixels (Figure 7).

Description	Friction Cost	Source	Area (% Aoi)[24]	Units
Huallaga River	0.0000320	Class II Rivers - WCS	1,022 km^2 (1.52%)	
Smaller Rivers	0.0000750	Class IV Rivers - WCS	6,284 km^2 (9.39%)	
Trocha	0.0008788	Field data regressions	1,672 km^2 (2.5%)	
Sin Afirmar	0.0004990	Field data regressions	259 km^2 (0.39%)	
Afirmado	0.0001247	Field data regressions	818 km^2 (1.22%)	Soles per sack per meter
Asfaltado	0.0000929	Field data regressions	259 km^2 (0.25%)	
No Bosque (= *Trocha*)	0.0008788	Field data regressions; Arima et al. 2007	7,261 km^2 (10.85%)	
Bosque	0.001858	20x higher than asfaltado (Arima et al. 2007)	49,451 km^2 (73.88%)	

Table 7: Friction values assigned for cost distance function.

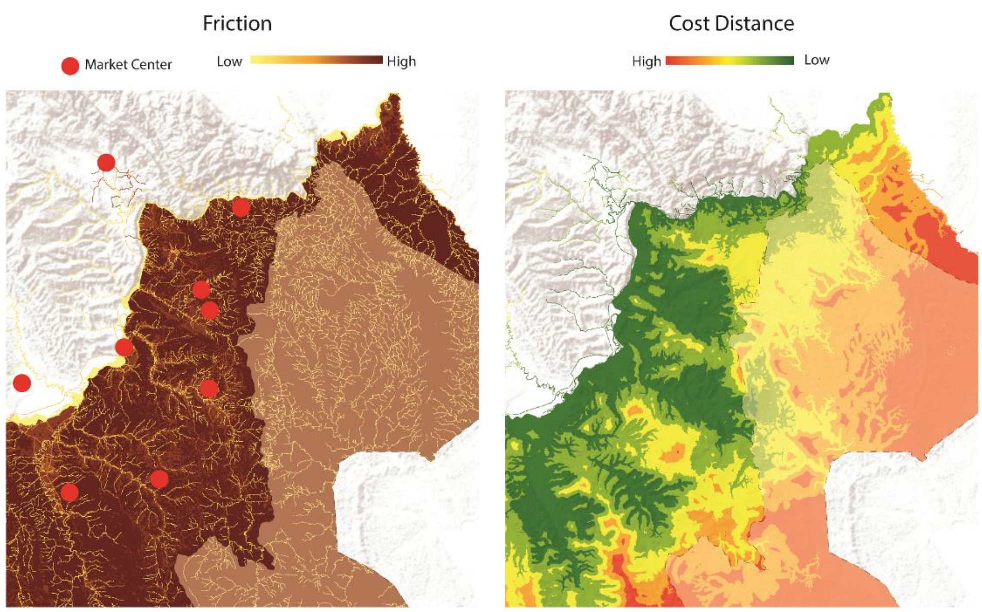

Figure 7: Cost distance modeling.

[24] Pixel counts and percentages were calculated *including only* the northwest buffer zone of Cordillera Azul National Park and *excluding* the park itself (nearly all forested pixels) as well as all areas outside the buffer zone, with the exception of the Huallaga River and major roadways (used for transport to market). If we include the park, 977,287 pixels in the study area remain forested. If process the study area simply as forested or unforested, 94,216 pixels appear as unforested—these include those pixels where roads and communities occur, etc.

Spatially Explicit Deforestation Probability

For the deforestation probability model, each raster (2-D matrix) was converted to a column vector variable while their location was tracked through an index ID number to ensure that each variable represented the same number of observations of the same spatial extent. A logistic regression was then run on the matrix including only those values (pixels) of interest for each variable according to the AOI matrix. For the purposes of the logistic regression, the control variable of soil was parsed out into 32 binary dummy variables, where 1 indicates that the soil is of the designated type and 0 indicates it is not.

Analysis	**Variable Group**	**Variable**	**Source**	**Type of Data**	**Expected Relationship**
Deforestation Probability Model	Dependent	Forest Cover	Hansen et al. 2014	Binary	N/A
	Independent	*ED*roads	CIMA Cordillera Azul, 2015	Continuous	Negative
	Independent	*ED*water	CIMA Cordillera Azul, 2015	Continuous	Negative
	Independent	Cost Distance	See below	Continuous	Negative
	Independent	*REP*	See above	Continuous	Positive
	Independent	Slope	ASTER GDEM	Continuous	Negative
	Control	Elevation Soil Type TRMM Park	ASTER GDEM Hengl et al. 2014 TRMM 3B43 CIMA	Continuous Binary Continuous Binary	Controls

Table 8: Key parameters used in the deforestation probability model.

Chapter 5: Results

DEFORESTATION PROBABILITY MODEL

As explained in the methods, the deforestation probability model took two forms—one which employed a cost distance variable as a proxy for freight cost, and another which employed Euclidean distance to roads and waterways. The logit regression involving the cost distance variable resulted in a final log likelihood of -233,130.1 with a pseudo R^2 equal to 0.0913. Of the seven original variables, nearly all displayed a highly significant ($p<0.001$) impact on the probability of whether forest is present or not. The only exceptions are two soil types, two of which—ferralsols and nitisols—have p-values equal to 0.47 and 0.96 respectively (Table 9). Of the explanatory variables, three displayed a negative relationship with the latent variable. Of these, cost distance exhibited by far the largest estimated impact ($z = -143.23$). Each 1 sol increase in cost from market (equivalent to 11.11 km on an asphalted road or 1.06 km on a dirt road) was estimated to decrease the latent variable by 0.3281 (Table 9). Taking logistic(y^*), the cost distance model yielded deforestation probabilities ($\hat{p}$) ranging from 0.002 to 0.922 per pixel, with a mean value of 0.22 (std. dev. = 0.1309). The spatial nature of these values is displayed in Figure 8, below.

In addition to this first logit regression, a second logit was run using Euclidean distance to roads and waterways. This model used the same number of observations as the previous model but replaced the cost distance variable with Euclidean distance to roads and waterways. The end result was a new equation where $y_i = 1$ (deforested) if

$$\beta_0 + \beta_1 ED_{roads} + \beta_2 ED_{waterways} + \beta_3 Population + \beta_4 Slope + \beta_5 Elevation + \beta_6 Soil + \beta_7 TRMM\ \epsilon > 0$$

This second logit regression resulted in a final log likelihood of -224,853.21 with a pseudo R^2 equal to 0.1235. Of the seven variables, four had a highly significant ($p<0.001$) impact on the probability of whether forest was present or not—namely, EDroads, EDwater, Slope, and Elevation. The non-significant effect of population (REP) is most likely due to the fact that both REP and EDroads use distance as a key component of their construction, and may be picking up the same effect, at least in part. Additionally, while the REP variable showed a positive effect in the cost distance deforestation model, it exhibited a non-significant, negative relationship with the latent variable in the Euclidean distance model due to its overlap with EDroads (Table 9).

Nearly all of the explanatory variables utilized in the Euclidean distance model displayed a negative relationship with the latent variable; the exceptions being several soil types and the precipitation variable. Of those variables that exhibited a negative relationship, EDroads exhibited the largest estimated impact by far ($z = -137.50$), followed by Elevation ($z = -49.57$), Slope ($z = -33.15$) and ED water ($z = -21.37$). However, compared with the cost distance model, the impacts of these variables seem to be much smaller. Each 1 kilometer increase in the distance from market is estimated to decrease the latent variable by 0.0004. A 1 kilometer increase in the distance from waterways is estimated to decrease the latent variable by slightly less, 0.0002 (Table 9).

Variable	Units	Coefficient (Std Err) Cost Distance Model	Coefficient (Std Err) Euclidean Distance Model
Pseudo R^2	-	0.0913	0.1235
Cost Distance	Soles per sack per m^2	-0.33 ($2.29E^{-3}$)***	-
EDroads	Km	-	$-4.77E^{-4}$ ($3.47E^{-6}$)***
EDwater	Km	-	$-1.58E^{-4}$ ($7.44E^{-6}$)***
Relative Effect of Population (REP)	Ratio of growth in population/distance from population	0.23 (0.02)***	-0.02 (0.02)
Slope	Degrees slope	-0.05 ($6.60E^{-4}$)***	-0.02 ($6.74E^{-4}$)***
Elevation	Meters above sea level	$-3.27E^{-4}$ ($1.62E^{-5}$)***	$-8.16E^{-4}$ ($1.64E^{-5}$)***
Soil			
Cambisols	N/A (Binary)	0.80 (0.03)***	1.05 (0.03)***
Ferralsols		-0.00 (0.01)	-0.13 (0.01)***
Gleysols		0.21 (0.03)***	0.39 (0.03)***
Histosols		0.81 (0.20)***	0.50 (0.18)**
Kastanozems		0.07 (0.01)***	0.01 (0.01)
Leptosols		-0.33 (0.03)***	-0.17 (0.03)***
Luvisols		0.14 (0.03)***	0.27 (0.03)***
Nitisols		-0.28 (0.39)	3.35 (0.40)***
Solonchaks		1.49 (0.02)***	1.80 (0.02)***
Umbrisols		-0.25 (0.04)***	-0.41(0.04)***
Vertisols		0.46 (0.22)**	0.57 (0.22)**
Acrisols		2.87 (0.40)***	3.05 (0.40)***
Precipitation (TRMM)	Average mm/year per pixel from 1998-2013	$+2.45E^{-4}$ (0.03)	$3.11E^{-5}$ ($1.86E^{-5}$)*
*p<0.1, **p<0.05, ***p<0.001.			

Table 9: Results of logit regressions.

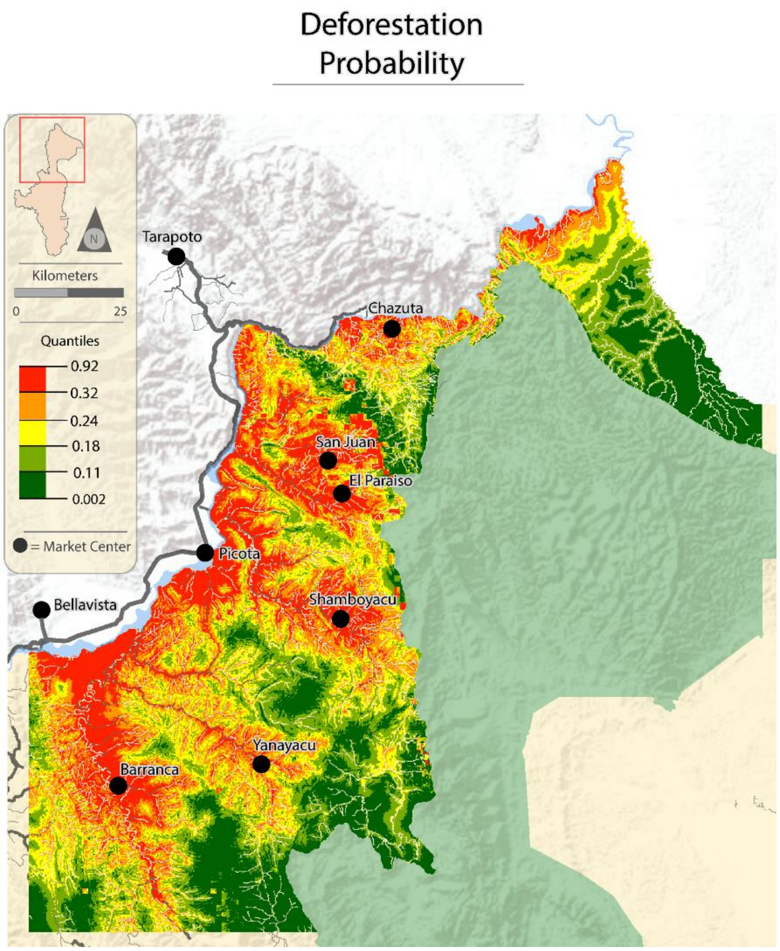

Figure 8: Deforestation probabilities across the AOI.

While the two deforestation probability models employed by this study indicated many statistically significant effects, this statistical significance may be due to the study's large sample size. To understand the practical significance of these results—i.e. the impact of each variable on deforestation probability—marginal effects are likely a more useful tool.

Table 10 displays the average marginal effects for each variable employed by both the cost distance and Euclidean distance models. Surprisingly, soil type displays some of the largest effects. However, these effects are likely minimized by the low percentage of most soil types within the AOI. While there may be an exception in the case of Acrisols, which represent both 47% of the AOI and have a larger marginal effect (0.56 and 0.55) on deforestation probability, these are clay-rich soils known for low fertility and toxic amounts of aluminum. Thus the marginal effect may be due more to prevalence than to benefits for agriculture.

Following soil types, the cost distance variable displays one of the largest effects. Each one point decrease in cost distance results in a 5% increase in the probability that an area will be deforested. This is followed by the REP variable, where each one point increase in the index results in a 4% increase in the probability that an area will be deforested. The marginal effects of these two variables within the cost distance model are larger than the effect of any (non-soil) individual variable in the Euclidean distance model. Within the Euclidean model, slope exhibits the largest marginal effect ($-3.42E^{-3}$), followed by the relative effect of population (Table 10). Though these marginal effects may seem small, it is important to note that the deforestation probabilities across the study area are also rather small, though accurate (mean = 0.22, which closely approximates the observed deforestation rate of 22.5%).

Variable	Marginal Effects: Cost Distance	Marginal Effects: Euclidean Distance
Cost Distance	-0.05 ($3.42E^{-4}$)***	-
EDroads	-	$-7.31E^{-5}$ ($5.09E^{-7}$)***
EDwater	-	$-2.44E^{-5}$ ($1.14E^{-6}$)***
Relative Effect of Population (REP)	0.04 ($3.59E^{-3}$)	$-3.05E^{-3}$ ($3.30E^{-3}$)
Slope	$-0.71E^{-2}$ ($1.02E^{-3}$)***	$-3.42E^{-3}$ ($1.03E^{-4}$)***
Elevation	$-0.50E^{-4}$ ($2.54E^{-6}$)***	$-1.25E^{-4}$ ($2.50E^{-6}$)***
Soil		
Cambisols	0.14 ($5.90E^{-3}$)***	0.20 ($5.94E^{-3}$)***
Ferralsols	$7.17E^{-5}$ ($1.49E^{-3}$)	-0.02 ($1.45E^{-3}$)***
Gleysols	0.04 ($4.40E^{-3}$)***	0.07 ($4.64E^{-3}$)***
Histosols	0.15 (0.04)***	0.09 ($3.33E^{-2}$)**
Kastanozems	0.01 ($1.67E^{-3}$)***	$2.26E^{-3}$ ($1.64E^{-3}$)
Leptosols	-0.05 ($4.42E^{-3}$)***	-0.03 ($4.80E^{-3}$)***
Luvisols	0.02 ($4.71E^{-3}$)***	0.04 ($4.80E^{-3}$)***
Nitisols	-0.04 ($5.27E^{-2}$)	0.58 (0.04)***
Solonchaks	0.29 ($4.83E^{-3}$)***	0.34 ($4.46E^{-3}$)***
Umbrisols	-0.4 ($5.90E^{-3}$)***	-0.06 ($5.49E^{-3}$)***
Vertisols	0.08 ($4.08E^{-2}$)*	0.10 (0.04)**
Acrisols	0.56 ($6.04E^{-2}$)***	0.55 (0.05)***
Precipitation (TRMM)	$0.39E^{-4}$ ($3.00E^{-6}$)***	$5.19E^{-6}$ ($2.89E^{-6}$)*
*p<0.1, **p<0.05, ***p<0.001		

Table 10: Marginal effects of the deforestation probability variables.

While the Euclidean distance model resulted in a higher pseudo R^2 than the model employing cost distance and may at first seem to be the stronger analysis, it was ultimately excluded from further analysis due to two main factors. First, the EDroads and REP variables both employ Euclidean distance as a factor and are likely producing a confounding effect. Second, and possibly because of this effect, the Euclidean distance model indicates a highly unlikely negative relationship between REP and deforestation. Considering that distance to the community is the denominator for the REP variable, this means that deforestation probability is expected to decrease the closer a given land parcel is to a populated, growing community center. Given these contradictions, the cost distance model is used for comparative analyses instead.

FOREST CONNECTIVITY CORRIDORS

As briefly prefaced in the methods, a least cost corridor function was run for each of the 91 unique forest patch pairs generated by this analysis. GIS operations were then used to select the lowest cost quintile from each of these individual corridors, and to aggregate a certain bottom percentage into one, equally-weighted raster. These operations were performed twice—once to yield a map of the lowest one percent of cost pixels (100 quantiles) and once to yield the lowest five percent of cost pixels (20 quantiles).

Given that the AOI for this study, corridor calculations were constrained to the buffer zone boundary. Of the 481,622 100-meter pixels in the buffer zone, 404,116 pixels (83.9% of AOI) are prioritized under a model that considers the bottom five percent in terms of pixel costs for each of the 91 corridors (remember that the lower the cost to traverse a pixel, the more valuable it is assumed to be, in this study, for a conservation corridor connecting forest patches). When the model is restricted further to include only the bottom one percent, the number of pixels shrinks to 215,974 pixels (44.8% of the study area) (Table 11). The spatial nature of this pattern is show in Figure 9, below.

Area	**No. of Pixels**	**% of AOI**	**Forested Cells**	**Unforested Cells**
AOI	481,622	100%	373,447 (77.5%)	108,175 (22.5%)
Corridors				
Bottom 5%	404,116	83.9%	323,039 (79.9%)	81,077 (20.1%)
Bottom 1%	215,974	44.8%	181,950 (84.2%)	34,024 (15.7%)

Table 11: Results from landscape connectivity corridor analysis.

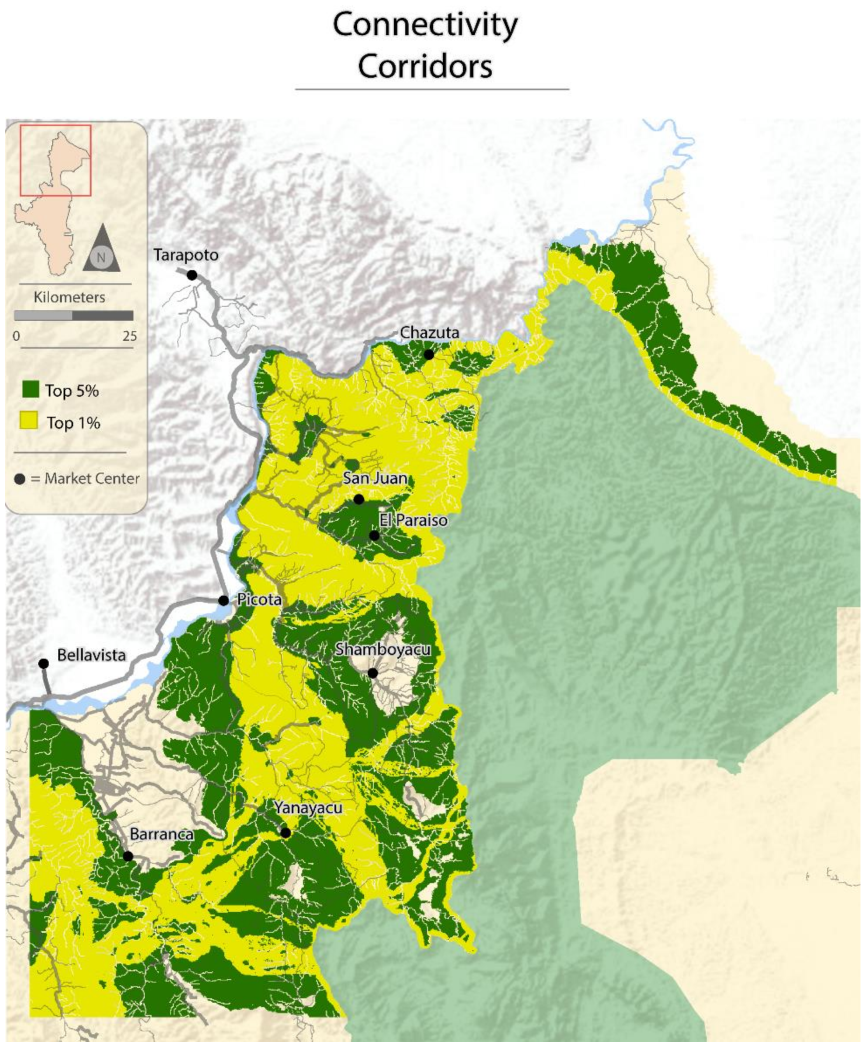

Figure 9: Top 5% and top 1% of connectivity areas across the AOI.

Given that a model prioritizing the bottom 5% of each corridor results in a vast majority of the area of interest (83.9%), this broader model was excluded from further analysis and comparisons and only the bottom 1% model was used.

CARBON

As described previously, data on aboveground carbon was obtained from the Carnegie Airborne Observatory at Stanford University (Asner et al. 2014). Within the

AOI, aboveground carbon density measurements range from 0.31 Mg C ha^{-1} to 146.74 Mg C ha^{-1}, with an average density of 56.10 Mg C ha^{-1}. Uncertainty in the area ranges from 0.32 to 30.81 with an average of 20.33 and a standard deviation of 1.57.

To identify areas of priority in terms of aboveground carbon, the top 1% and the top 20% of aboveground carbon density values were isolated. Of the 481,622 100-meter pixels in the buffer zone, 97,021 pixels are prioritized under a model that isolates the top 20% of pixels in terms of aboveground carbon density. These pixels have an average ACD of 110.68 Mg C ha^{-1}, and an average uncertainty of 25.79. When this model is restricted to include only the top 1%, the number of pixels shrinks to 4,380 pixels with an average ACD of 130.85 and an average uncertainty of 26.96 (Table 12, Figure 10).

		ACD (MgC ha−1)			Uncertainty			
Area	**Pixels**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**SD**
AOI	481,622	0.31	146.74	56.10	0.32	30.81	20.33	1.57
Top 20%	97,021	98.00	146.74	110.68	25.97	30.81	25.79	6.69
Top 1%	4,380	128.00	146.74	130.85	26.92	30.81	26.96	7.68

Table 12: Results from aboveground carbon density (ACD) prioritization.

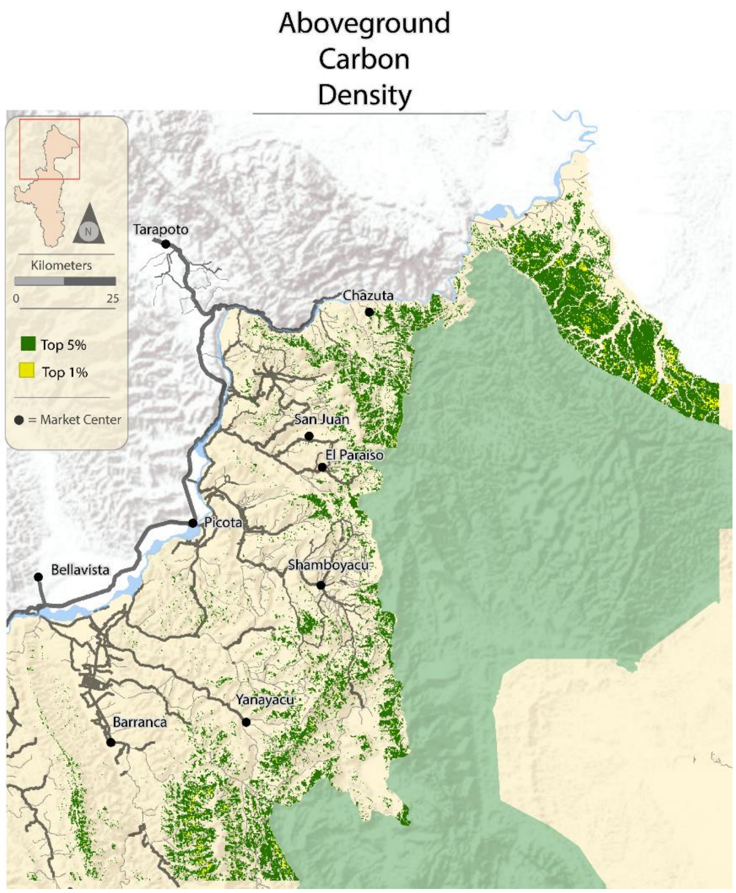

Figure 10: Top 20% and 1% areas in terms of ACD.

COMPARATIVE RESULTS

Spatial intersections of the three models were conducted using the middle most quintiles of deforestation probability, the top 20% of ACD and the lowest 1% of corridors as these yielded samples of relatively similar sizes (Table 13). Given that the model for aboveground carbon density isolated the lowest number of pixels (97,021), this model acted as the limiting factor in determining the maximum number of pixels that could possibly meet all three criteria.

Model	No. of Pixels	% AOI	Selected Areas
ACD	97,021	20.0%	*Top* 20%
Deforestation Probability	191,998	40.0%	*Middle* 3rd and 4th quintiles [25]
Forest Connectivity	215,974	44.8%	*Bottom* 1%

Table 13: Results from all three schemes of conservation priority.

Spatial intersections were performed for all three models, as well as all 2-model combinations. Results vary substantially. Figure 11 shows the number of pixels isolated by each intersection, the maximum possible (97,021) and the proportion of forested/not forested pixels. The intersection of all three criteria resulted in 11,894 pixels. In contrast the intersection of just carbon density and corridor areas resulted in the a set of 38,695 pixels, just carbon and deforestation resulted in 22,297 pixels, and just corridor and deforestation priority areas resulted in the isolation of a striking 91,235 pixels. Maps showing the spatial configurations of all four comparisons are shown in Figure 12a-d.

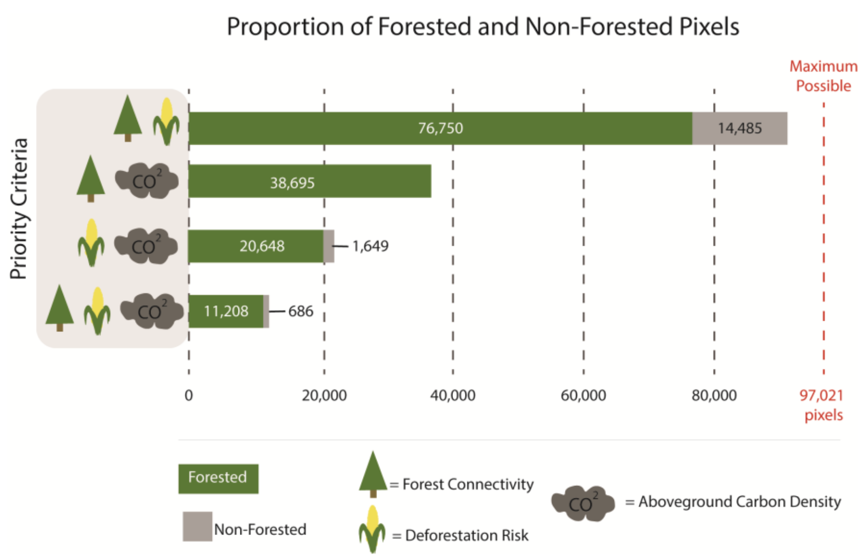

Figure 11 Forest and non-forest in the four priority schemes.

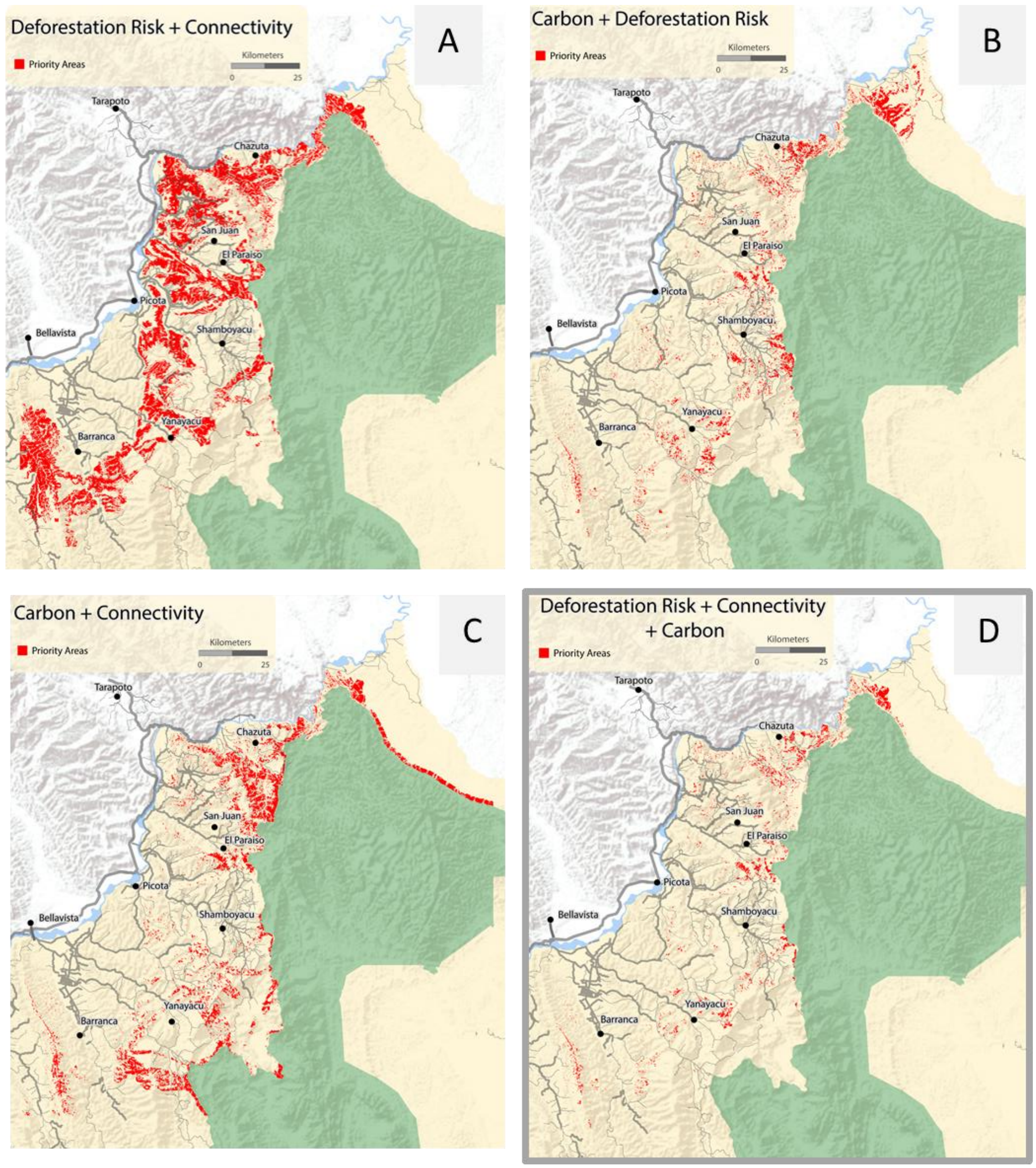

Figure 12 Results from all four conservation priority schemes.

Chapter 6: Discussion

This thesis implements three sets of models, as based on aboveground carbon density, forest connectivity and spatially explicit deforestation probability, in an effort to inform conservation initiatives in the buffer zone of Cordillera Azul National Park, Peru. In doing so, it provides valuable information for conservation planners, park officials and investors. The discussion below addresses the nature of these spatial configurations, and implications for cost effectiveness, additionality, and tradeoffs. It concludes with a discussion of computational and contextual challenges and constraints, followed by opportunities for future research.

SPATIAL NATURES

Forest carbon offsets are a popular tool for conservation finance. However, while carbon offsets may help reduce carbon dioxide emissions, priority areas for carbon offsets may also differ spatially from other key conservation objectives. As seen in Figures 8, 9, and 10, each of the individual criteria isolate a substantial subsection of the AOI (Figure 12a-c). However, when one attempts to strike a compromise between all three criteria, the priority conservation area shrinks substantially (Figure 12d).

An intersection of the three prioritization schemes results in an overlap of just 11,894 pixels. This is under 3% of the area of interest and represents 12.3% of the potential compromise area.[26] If all three objectives are to be pursued, these pixels represent the priority areas for investment. However, while 94.2% of this area was still classified as forested as of 2013, thus offering opportunities for conservation and/or

[26] Remember that the number of pixels under a scheme that meets all three criteria is limited to the pixel count in the smallest model (97,021 pixels according to the ACD 20% priority model).

offset programs, these pixels are also scattered across the AOI. A main cluster stretches from Chazuta northward, between the Huallaga River and the park's northernmost peak, while smaller clusters are scattered around the outskirts of Yanayacu, and along the park boundary in the central AOI.

Given this sparse distribution, a strategy focused on isolating these areas as stand-alone targets may in fact be less effectual than anticipated. Specifically, the small overall size and largely dispersed nature of this pattern suggests that a conservation strategy that prioritizes only those areas that meet all three criteria may paradoxically undermine one of them—forest connectivity. To compensate for this fact, conservation initiatives following this scheme would be wise to focus on restoration of nearby areas or the creation of a landscape mosaic that is more environmentally friendly. For instance, farmers could be encouraged to grow cacao, coffee or other agroforestry crops in the surrounding area.

An additional strategy lies in the community partnerships CIMA has made. Since the early 2000s, CIMA has been actively working with communities in the park buffer zone to establish communal living norms, community values, and conservation strategies. However, while many of these partnerships have been successful, CIMA staff have also reported difficulty with establishing and maintaining partnerships with the area's growing migrant population. Given that many of these smaller clusters center around just such areas—Sangamayo and Porvenir are two examples—devising new strategies to incorporate these stakeholders will be an important step. This is true even for those areas that have yet to be occupied (such as up north). Due to the high rates of inmigration, the buffer zone's social landscape can change frequently and dramatically. Any conservation strategy based on this intersection would need to be paired with a modification of CIMA's current methods and techniques, to further incorporate diverse stakeholders and new participants, including those who may be unfamiliar with the natural processes of the area.

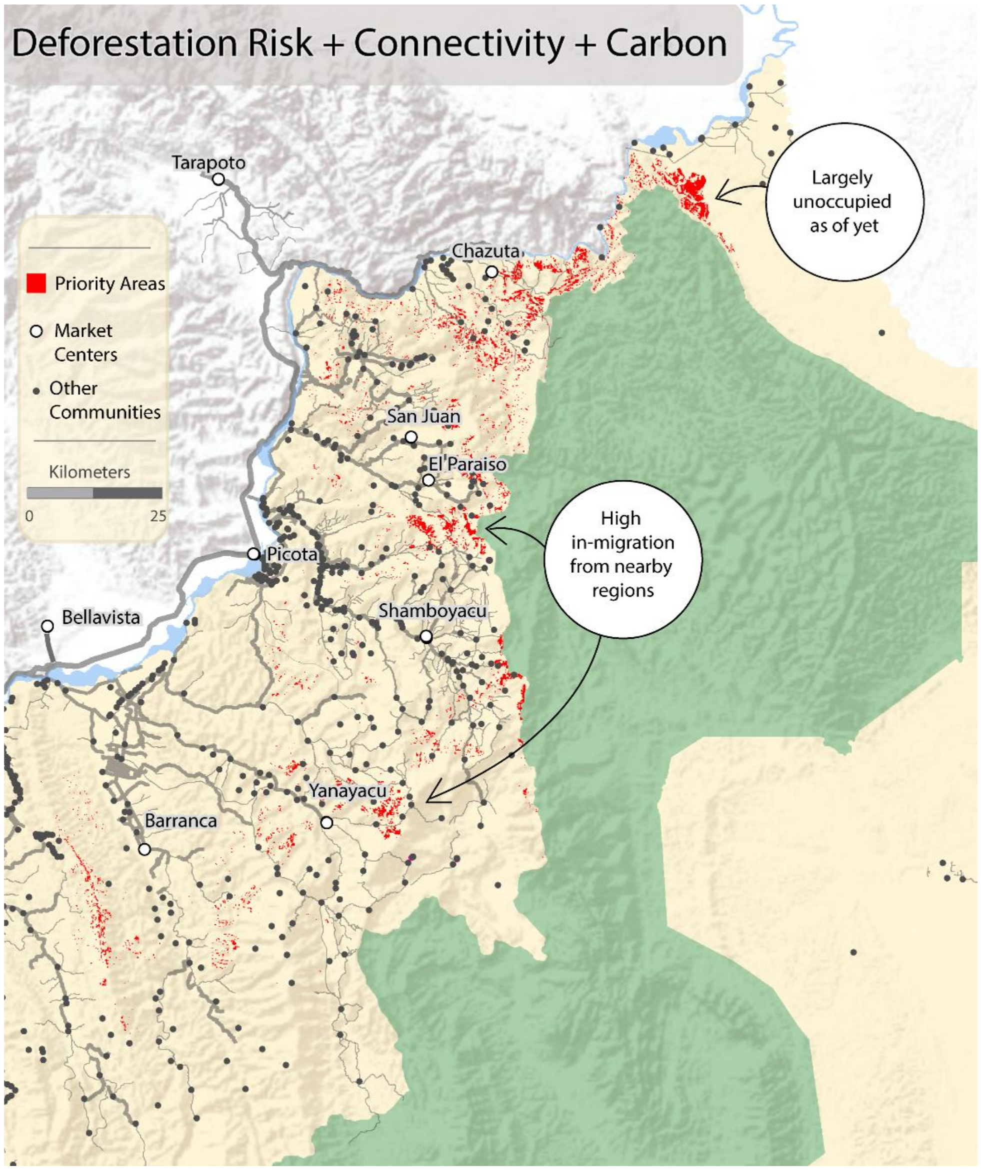

Figure 13 The larger landscape of a tri-criteria conservation plan.

In addition to adjusting their community base, CIMA Cordillera Azul and other conservation practitioners could also expand the priority criteria to include all areas that meet two of the criteria, rather than all three. In the case of Cordillera Azul National Park, a model that prioritizes both high aboveground carbon density and deforestation probability is the one most likely to be used for a carbon offset program. This is due to the fact that for a carbon offset project to be verified, it must prove both high above ground carbon density and additionality.

Figure 14 shows the spatial nature of (a) a conservation scheme that prioritizes high ACD and moderate deforestation probability, alongside (b) one that prioritizes deforestation and forest connectivity corridors. While there is some overlap between the two, one can also observe that the latter not only prioritizes more area (91,235 pixels versus 22,297 in the former model), but also allows the model to protect connective pathways with PNCAZ itself.

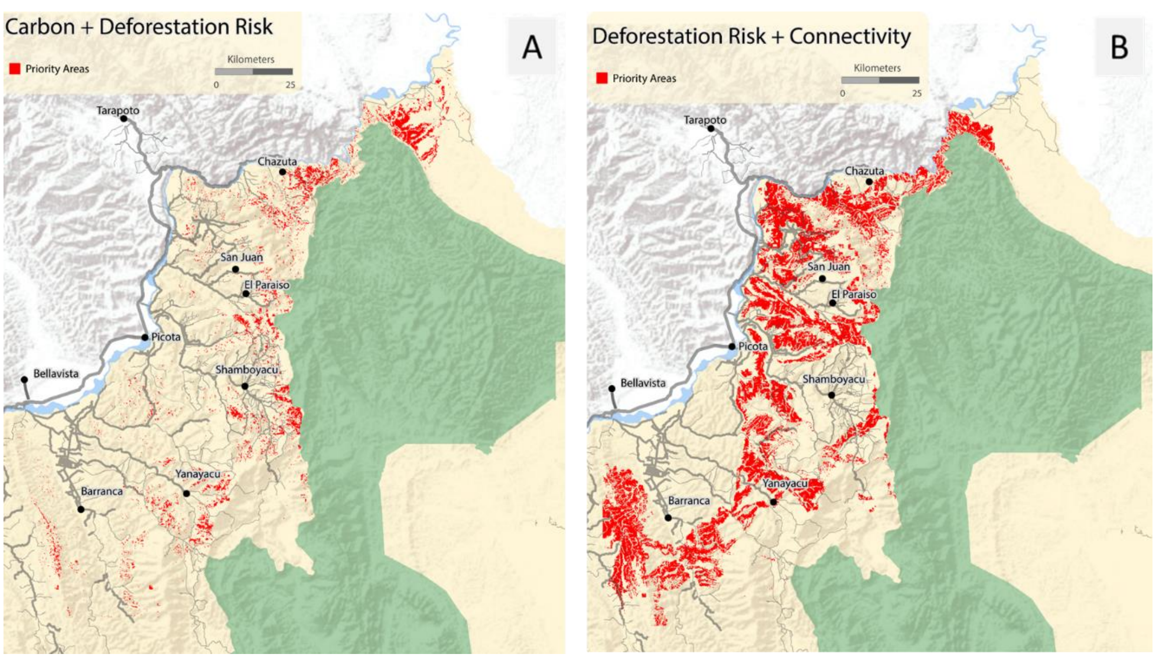

Figure 14 Deforestation and carbon vs. deforestation and connectivity.

COST EFFECTIVENESS & TRADEOFFS

By assigning priority to those pixels that fall within the top 20% of aboveground carbon density and are also within the 3rd or 4th quintile in terms of deforestation probability, the first map above (Figure 14a) isolates pixels that are expected to experience moderate deforestation risk, and are thus eligible for carbon dioxide emission reductions (i.e. offsets). Because these pixels are not among the highest in terms of deforestation risk, they are also unlikely to represent the areas of highest profitability and are thus more cost effective for carbon offset investors and conservation practitioners to target.

However, while this model may be the best in terms of expected cost-effectiveness, it does differ spatially from forest connectivity, a factor that should not be overlooked. Maintaining landscape connectivity is a key strategy for conserving species diversity under changing climatic conditions (Bernazzi et al. 2012, Staudinger et al. 2012, Gilbert-Norton et al. 2010, Heller & Zavaleta 2009, Tischendorf & Fahrig 2000). While historically species have used large-scale movement to adapt to climatic changes (Martinez-Meyer et al. 2004; Parmesan & Yohe 2003), species today are expected to face larger migration distances (Schloss et al. 2012) across larger anthropogenic barriers (Sanderson et al. 2002) than species of the past. Species may also be required to migrate faster (Malcolm et al. 2002),[27] adapting to novel climates that develop at the same time that other climates disappear (Loarie et al. 2009, Williams & Jackson 2007).

As of 2006, altitudinal or longitudinal range shifts had already been observed in over 1,000 species as of 2006 (Parmesan 2006). Though PNCAZ encompasses a large altitudinal gradient (approx. 200-2400 meters), tropical montane ecosystems are expected

[27] Williams & Jackson (2007) predict that novel climates will develop primarily in the tropics and subtropics, whereas disappearing climates will concentrate in tropical montane regions and the poleward portions of continents.

to have a harder time adjusting to shifts in climatic gradients (Feeley et al. 2013, Feeley et al. 2011, Feeley & Silman 2010, Foster 2001). If climate change continues, the protection provided by the park may not be enough.[28] After all, PNCAZ and similar areas exist within larger environments of human disturbance (Laurance et al. 2012, Chazdon et al. 2009, Lovejoy 2006). Species within these areas may attempt to shift their range in line with climate transitions only to find that their movement is inhibited by the spread of anthropogenic land use in the surrounding area (Burrows et al. 2014, Nuñez et al. 2013, Coristine & Kerr 2011).[29] Deforestation, roads and frontier communities are all barriers to connectivity that these species would have to face (CIMA 2012, 2013; SCSGS 2013).

Considering current migration barriers, and the park's high rates of endemism, landscape connectivity will likely play a large role in future climate change susceptibility. However, while forest carbon offset markets have helped establish the three criteria of additionality, leakage, and permanence in terms of carbon, little to no work has been done to classify and validate the services that forest connectivity offers.

IMPORTANT CONSIDERATIONS

REDD+ and similar offset mechanisms operate on the assumption that by generating alternate employment options and new income opportunities, they can reduce deforestation pressures at the forest frontier. One common determinant of an area's eligibility for a carbon program is the area's capacity to experience reduced deforestation at a low cost (Andersen et al. 2012). However, estimating these costs can be difficult. Changes in landscape can be attributed to a combination of factors, including

[28] Under climate change, some species declines are expected even in the absence of dispersal barriers (Pereira et al. 2010). One recent study by Ceballos and colleagues (2015) has indicated that current extinction rates vastly exceed natural background rates. According to this data, the authors suggest that we may be entering a sixth mass extinction (Ceballos et al. 2015). In biodiversity hotspots—such as tropical Peru—extinction rates of endemic species are predicted to be even worse (Malcolm et al. 2006).

[29] See Dutta et al. (2015)'s "Connecting the dots: mapping habitat connectivity for tigers in central India" for a more specific example on this.

environmental heterogeneity and variability (Gustafson 1998, Turner et al. 1995), population growth, demographic transitions, technological innovations or political developments (Rounsevell et al. 2003, Walker et al. 2002, Stoate et al. 2001), as well as resultant economic conditions (e.g., Irwin & Geoghegan 2001, Kaimowitz & Angelsen 1998). Because of this, at least two scales are at work. The first, a microscale, is highly affected by the objectives of individuals acting on the landscape (i.e. their economic incentives or cultural preferences). The second, a macro-scale, stems from the context in which these decisions are made (Brown et al. 2012, Geist and Lambin 2002 & 2001, Kaimowitz & Angelsen 1998).

While this study attempts to address the latter, little information was available to appropriately explore the former. Accessibility to markets (i.e. freight costs) was used as a proxy for the spatial variation in prices; forest structural connectivity was used as a proxy for process connectivity. Given this level of analysis, exact opportunity costs, household and ecosystem level data, social and cultural differences, and time series information are incomplete. Additionally, any true measure of connectivity must be based on movement of an organism through a landscape. Since this study was unable to incorporate many of these components, they would undoubtedly be useful for future research. Implications for this study are briefly addressed below.

Caveats of Economic Rent

While the deforestation probability model presented by this study attempts to capture the economic landscape, several caveats should be noted.

First, by not employing actual market prices for products, this model cannot calculate exact opportunity costs for a given land use at a given land parcel. However, had current market prices been used to calculate deforestation probabilities, the analysis would have been fixed to a specific set of market conditions at a specific time (i.e. the present). Costs of reducing deforestation would have been assumed to be equal to the current value of the land for whatever production is occurring.[30] By using freight costs to approximate deforestation probability, the values determined by this study instead form a type of index. Each value holds true and remains adjustable as long as prices fluctuations for different market goods do not change relative to each other.

Second, by using road location and condition as a factor in determining deforestation, the model also runs the risk of endogeneity as road location may actually be influenced by the location of agricultural production. Chomitz and Grey tested for this possibility in their 1996 study, and found evidence of the endogeneity of roads. Although this study controlled for a rich set of variables that may be correlated with road placement (e.g. slope, elevation, soil type), road endogeneity cannot be ruled out completely and the estimate of the influence of accessibility on deforestation may be overstated.

Third and finally, the area of interest presented by this study is still affected by at least two unlawful forces: illicit land grabs and the production of illicit crops (see Appendix for more information). Rather than exhibiting the traditional model of economic rent, which exhibits a positive correlation with proximity to market (see Figures 2 and 3, Chapter 3), illicit activities follow a slightly different pattern. In the case of illicit crops and land grabs, areas of high rent are those out of sight rather than those centrally located. This is due to that fact that illicit activities require areas where there is the highest chance to avoid detection (i.e. the lowest chance of being seen). Thus, the most profitable areas are those absconded from the view of roads, markets, communities, perhaps even within patches of intact forest. Figure 15 illustrates how this speculative inverse relationship might look.

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[30] i.e. if the land is currently a logging concession, cost of reducing deforestation would be equal to the opportunity cost of not logging, or the profits from the logging itself.

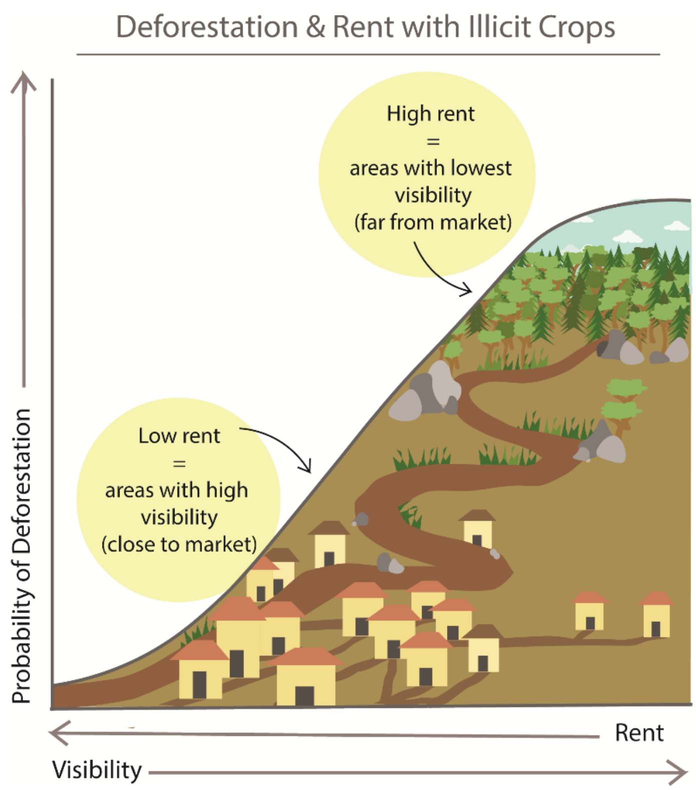

Figure 15: Deforestation, rent and visibility in the case of illicit crops.

Limits of the Landscape Level

Considering the caveats above, models based on landscape-level factors could be greatly improved by additional information. For instance, while the deforestation model's basis in economic rent and deforestation probability attempts to address the heterogeneous nature of the landscape, the model also overlooks important micro-scale information. For the purpose of this study, the explanation below divides this information into two categories: (1) agents, defined here as decision-making individuals that are acting upon the landscape, (2) broader contextual information on the area.

Agents

In a large and/or heterogeneous region, different agents may be active in different areas. These dynamics, whether among agents or between agents and their environment, are important components of land use and land cover change (Geist and Lambin 2001), and ultimately add spatial complexity to any attempt at causal explanation (Walker et al. 2002).

For instance, if agroforestry crops prove profitable, a farmer may decide to expand their farming operation. This can either occur through increased production on the same amount of area, or by expanding crop production onto new tracts of land. Additionally, while models may predict deforestation will occur in a certain pattern given this profitability, the actions of neighbors and communities can impact the land use decisions of individuals in unexpected ways. As one neighbor witnesses another profiting (or losing money), their land use decisions may change.

Programs can have a similar effect. For instance, carbon offset programs that displace previous landowners (e.g. subsistence farmers, cattle ranchers), may result in indirect land use change as the displaced individuals colonize new areas for cattle and farming. In carbon market jargon, this effect is classified as "leakage" and forms an important criteria for program validity (see Chapter 3 for definition).

Contextual Information

As described above, while landscape-level models for conservation may make priority areas easier to identify, they can also overlook important local variations. In the case of the forest connectivity model, this overlooked information is the difference between structural connectivity and process connectivity. While forest intactness and patch connectivity are important components of ecosystem functioning, species abundance and distribution, and ecosystem functioning are all equally, if not more, vital.

Without habitat level information, these landscape models can only broadly and roughly approximate connectivity (Tischendorf 2000).

In similar fashion, economic rent may not directly model the actual land-use transitions of an area. The buffer zone of PNCAZ is in many ways an agricultural frontier. While market prices help determine the opportunity costs for standing forests and incentives for clearing (Bowman et al. 2012, Poffenberger 2009, Chomitz et al. 2005), land markets and the social and cultural factors affecting them also have a large impact.

Despite the fact that land tenure, titles, and records are often scarce,[31] land transactions occur regularly in the Cordillera Azul buffer zone. A recent study near Cordillera Azul reported that despite only 2% of respondents holding a registered land title, over 300 land transactions were reported. While landowners in the area likely experience higher risk due to the lack of land tenure (and thus expect lower profits) recent transactions indicate that the cost of purchasing land rose by 11-26% each year between 2003 and 2013. In some cases, lack of land tenure may have even encouraged these sales, as informal purchase agreements between the buyer and seller helped create a paper trail to indicate ownership (Holland & Coomes in review).

While many of these sales occur legally, there is also the aforementioned component of land trafficking. In the Cordillera Azul buffer zone, land traffickers often travel from San Martin to the Sierra region to sell the land, which Serrano buyers then relocate their households to claim. Because of this trend, in-migration to the area is increasing. A recent study on land markets in the area found that 92% of respondents were born elsewhere in Peru, and 60% had arrived in the last ten years (Holland &

[31] Of the agricultural land in the entire department of San Martin, only about 30% has a registered land title (Conservation International 2011, Gobierno Regional San Martin 2009). In the northwest buffer zone of Cordillera Azul National Park, this percentage is even lower (CIMA 2012).

Coomes in review). [32] Thus, while economic rent is likely a key factor in modelling deforestation, there are likely numerous other factors underlying the "who", "where", "why" and "how" of land market transactions.

Given that many of these social and cultural characteristics vary at the household level, failure to incorporate survey-based information about household and community structures can also create specification bias (Walker et al. 2002). For instance, past studies indicate that farmers identify opportunity costs in vastly different ways. While some farmers identify the minimum compensation to not deforest as almost twice their net agricultural revenues (Leguia et al. 2011), others indicate a willingness to pay to conserve forest (Gomez et al. 2013).

These discrepancies also have large implications for the cost effectiveness of carbon programs and may reflect larger implementation challenges. For farmers and landowners who are not financially indifferent, offset mechanisms that pay them equal to their opportunity cost (i.e. that provide a financial incentive equal to what they would have received using the land business-as-usual) result in a net benefit experienced that is functionally zero (Andersen et al. 2012). In such cases, positive benefits to land owners only arise when they are paid *more* than their opportunity cost of not using the land.

Additionally, despite the time farmers gain by receiving carbon payments—and thereby, additional potential income—concerns about food security, self-sufficiency, or a preference for familiar agricultural revenues can cause farmers to prefer agricultural work over equal income from forest conservation (Andersen et al. 2012). Land owners accustomed to one form of land use may perceive alternative forms as risky, thus requiring further payment to offset their uncertainty or justify the time spent learning new

[32] In a place like the Huallaga Valley, with high rates of in-migration and some swathes of intact, unclaimed forest, tenure of new lands is also often established by the slashing and burning of forest—i.e. tenure by deforestation. This is an important piece of examining environmental impacts and will be discussed in detail later.

practices. In contrast, willingness to pay can stem from farmers' awareness of, and appreciation for, preserved forest and the ecosystem services it provides (Gomez et al. 2013).[33]

An understanding of these beliefs and preferences is important for the appropriate analysis of any conservation priority model. Depending on local conditions, high compensation demands may be the result of farmers underestimating their labor costs and thus overestimating net revenues, indicating larger social issues. In addition, firms that invest money without such knowledge may be unintentionally selecting one stakeholder over another. While the model for deforestation probability selects those areas that are expected to be most cost effective, the *who* of these areas remains a mystery. If based on additionality and cost effectiveness alone, financial incentives may overlook community-run forests that, though highly productive, are not part of a formal market (Griffiths 2008). In this way, economic influxes from carbon markets have the potential to selectively support conventional developments, ultimately harming low-carbon livelihoods while doing little for local transitions to a carbon-free economy (Lohmann 2009).[34, 35]

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[33] Research on tenure shows similar contradictions. While some studies indicate that areas with individual land titles are more likely to be deforested than communally owned lands or public lands (Andersen et al. 2012), others point to the fact that in areas where land rights are lacking, deforestation is often a tool to establish ownership (Angelsen 1999).

[34] One powerful example of how social inequalities can become reinforced is the use of monoculture oil palm plantations in carbon credit projects, which have contributed to the displacement of communities and ecosystems in the name of carbon sequestration (Koh and Ghazoul, 2008).

[35] While less relevant for the purposes of this study, one of the most common critiques of carbon markets is that they abstract the "where", "how", "when" and "by whom" of carbon emissions cuts and may promote a set of *laissez-faire* capitalist ideas (Matulis 2014, Lohmann 2012, Lohmann 2009, Griffiths 2008). By making carbon emissions a commodity—and thus a nearly tangible asset to be bartered over—scholars assert that carbon markets secure the background conditions necessary for carbon accumulation and promote the generation of carbon emissions for trade and commerce (Lohmann 2009). As Lohmann (2009) so eloquently states, "climate solutions are then disembedded from history and technology—from whence long-term solutions would emerge—and are re-embedded into the realm of economics, trade theories, and property law". Thus, while commodification may help with quantifying and regulating emissions, the long-term effects may be something much darker; namely, the reinforcement of business as usual and the stifling of any new systems or sparks of innovation.

In addition to all challenges outlined above, carbon markets may also have larger, society-level impacts. The large sums of money associated with carbon offsets can split indigenous peoples' advocacy movements, dividing those who see carbon as an opportunity for advancement from those who see it as an 'enclosure movement' (i.e. the process to end traditional rights) (Griffiths 2008). Environmentalists may experience similar divides, with those in favor of large, Washington-based actors such as Conservation International and The Nature Conservancy on one side, and those who see REDD as disempowering forest peoples in favor of corporations on the other (Griffiths 2008). Furthermore, some scholars posit that there is an inherent, inequality of opportunity in emissions trading (Page 2012). This can manifest as inequalities of bargaining power and has immense implications for the resulting moral relations among climate governors of the future (Page 2012).

FUTURE WORK

Today, conservation practitioners are faced with the challenge of designing financially viable conservation programs that protect biodiversity, mitigate climate change, offset deforestation, and contribute to local livelihoods. This is an enormous task and one that should not be taken lightly. While this research presents an initial case study towards this end, future advances in data will undoubtedly support further research.

Deforestation literature has long recognized interactions between loggers and follow-on farmers (Rudel et al. 2002, Walker 1987) and there is increasing evidence that prior development is associated with negative feedbacks (Irwin and Bockstael 2002). Constant model parameters can produce misleading R^2 values and t-statistics. While time series data were limited for this study, incorporating a temporal dimension in the future would likely help approximate these effects. Specifically, future models could employ econometric methods for panel analysis to allow a variable relationship between independent and dependent variables (Hsiao 1986).

In addition to methodological progress, the future will also bring higher quality data. The SoilGrids data used by this study is set to be released at even higher resolution (250m) later this year. In addition, new carbon datasets promise to unlock research questions that have been stymied for years by an unknown “where” and “how much” of terrestrial carbon (Pelletier et al. 2011). Asner et al. (2014) have already begun to provide carbon data at the 1-hectare level. In countries like Peru, which harbor large bioenvironmental gradients and undergo rapid land use change, such data is invaluable for mitigation and valuation strategies. By providing data at the hectare scale—the world’s most common unit of land tenure and an important scale for regulatory policies—Asner and colleagues (2014) have opened the door for future merging of the micro and macro scale.

Chapter 7: Conclusion

Within the 2011-2016 Master Plan for Cordillera Azul National Park is a vision for the park's future. By the year 2028, the goal is that PNCAZ will be a national protected area that wholly conserves its biological diversity, is participatory managed, is financially sustainable, and supports the betterment of quality of life in neighboring communities.[36] To do so, the PNCAZ and its current governing bodies—namely, CIMA Cordillera Azul—will need to find ways to maximize multiple criteria for conservation. In a 2014 report, CIMA Cordillera Azul stated that other than the anticipated sale of carbon credits, there is no source of income for the restoration and deforestation offsetting activities planned under the carbon project (CIMA 2012, 2013; SCSGS 2013).

However, while forestry carbon offset projects have the potential to sequester and store carbon, protect water resources and biodiversity, and offer economic opportunities, successfully designing programs that can do all three remains a challenge. Towards this end, this research uses a recently released high resolution carbon dataset (Asner et al. 2014) alongside frameworks of deforestation probability and landscape connectivity to examine the potential for multi-objective landscape planning. The study employs a modification of least cost path to examine forest patch connectivity and uses this methodology to isolate the subsets of each forest patch corridor that represent the lowest 1% in terms of cost. It also puts forth a new, spatially explicit model for deforestation in the area. Based on economic rent, the model prioritizes those areas that are cost effective

[36] Paraphrased in English from the original text: "Para el ano 2028, el PNCAZ es un ANP que conserva integramente su diversidad biológica, es gestionado participativamente y como tal reconocido a nivel nacional e internacional; cuenta con sostenibilidad financiera y contribuye a la mejora de la calidad de vida de las poblaciones vecinas a través de las oportunidades que ofrece y su vex posibilita un desarrollo sostenible y planificado de su ZA" (page 24).

for conservation by identifying where there is both moderate deforestation risk and limited profitability. These conceptual models are then applied to a subregion of the Cordillera Azul buffer zone. There, they are intersected with the carbon dataset to determine how the three conservation priority schemes vary spatially, and if commonalities can be found between the distinct criteria.

The deforestation model used in this study expands on previous baseline studies in the area by incorporating biophysical, social and economic variables. The result is a spatially explicit map of deforestation probabilities across the study zone that can be used for carbon offset projects in years to come. In addition, by incorporating the theoretical frameworks of economic rent and landscape ecology, this work presents new models for the study area and also provides new theoretical ground for the spatial analysis of multi-criteria conservation planning schemes. Through its comparative analysis, the study finds that planners can design a configuration that prioritizes all three criteria.

However, while the three criteria can be maximized simultaneously, this research also shows that in the case of Cordillera Azul the result may be just a small subset of the overall landscape. Considering this, a conservation scheme seeking to prioritize all three criteria would be wise to expand upon these results. CIMA Cordillera Azul (or similar conservation stakeholders) could extend their work to new communities in the buffer zone area. Additionally, areas that meet two of the three criteria could also be selected for secondary priority and targeted for increased efforts. Generating new levels of participation across the buffer zone communities and promoting connectivity-generating activities (e.g. agroforestry) outside the priority subset, would undoubtedly further such conservation efforts.

In closing, despite all the caveats in the previous chapter, the methodology used by this work is useful for mid-scale landscape planning. As awareness of climate change grows, carbon programs and similar mechanisms are likely to gain in popularity. In 2009, Lohmann estimated carbon market trade at over US$100 billion annually. He also estimated that these numbers would rival other major markets—such as that of financial derivatives—within a decade (Lohmann 2009).

So far, Lohmann's predictions seem to be holding true. In 2013 alone, eight new carbon markets opened their doors (World Bank 2014)[37] and today carbon emissions remain the focus of both pollution reduction schemes and climate change mitigation strategies. While some of these take the form of regulations on fossil fuel industries, many more target deforestation and forest degradation—largely believed to be a less costly target (Naucler & Enkvist 2009, Antorini & Sathaye 2007, Stern 2006). Analyses such as the ones presented by this study will be useful as CIMA and other institutions work to improve offset initiatives and better target their efforts. If placed in the right hands, these models can then be improved upon through expert information, household data and survey work for improved accuracy and success.

As pressures to mitigate climate change and protect forests cost effectively continue, policymakers and conservation practitioners will be faced with some difficult decisions. Tropical country interventions seeking to simultaneously reduce deforestation, protect biodiversity, and improve livelihoods entail complex socio-environmental trade-offs (Andersen et al. 2014). Many 'incentive schemes' may overlook the inherent complexities of these systems (Pascual et al. 2014). By incorporating three unique frameworks for mid-scale planning, this research takes an essential step in determining if, and how, conservation may find peace among all three pillars.

[37] The 8 new programs as of 2013 include California Cap-and-Trade Program, Québec Cap-and-Trade System, Kazakhstan Emissions Trading Scheme, and five Chinese pilot emissions trading schemes (Shenzhen, Shanghai, Beijing, Guangdong, and Tianjin).

Appendix

A Brief History of San Martin

Throughout the history of the Huallaga Valley, economic rent has played a fundamental role. After coca/cocaine was largely eradicated, large-scale agriculture—particularly oil palm, rice, bananas and papaya—drove the demand for land in the region.[38] While not the same as coca/cocaine profits, big agriculture still supplied smallholders with greater returns than traditional, localized farming methods. However, while coca/cocaine required a smaller harvest area to achieve a high profit, other forms of agriculture often required farmers to clear more land in order to achieve the same returns (Bradley and Millington 2008). In order to steer farmers into more sustainable farming without sending them into poverty, USAID and the Peruvian government had to offer equal—if not better—financial alternatives. These alternatives first took the form of coffee and cacao, followed shortly by the rapid expansion of forest carbon offset projects.

1970-2002: Coca, Alternative Development and PNCAZ

The region of San Martin lies in the heart of Peru. Nestled between the high peaks of the Andes and the jungle of the Amazon, it is renowned for its bountiful nature, beautiful people, and delicious food. It is the most productive department in Peru in terms of agriculture (Gomez et al. 2013), and often promotes itself as a globally recognized model for sustainable development (Cabieses 2010). [39] However, San Martin was not always this way. Beginning with the displacement of indigenous peoples when the area

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[38] It should be noted that while large scale agriculture may have certain factors that affect the price of land (such as access to roads and markets), these factors are often different for illicit crops, which farmers often attempt to hide from view (i.e. the same roads and market centers).

[39] Conservation International has a project page for the area, outlining sustainable development initiatives, as do many other similar institutions: http://www.conservation.org/projects/Pages/Developing-a-Sustainable-Economy-in-San-Martin-Peru.aspx

was first colonized, the region has undergone numerous boom and bust cycles. Since the 1970s, many of these have been tied to agriculture both legal and illicit, and have had a heavy influence on land use development in the area.

Figure A1 shows some of the main agricultural, and later carbon and forestry-related, events from the 1970s through present day. While San Martin experienced steady in-migration of peasant farmers during the 1950s, 60s, and 70s, it had a completely different draw ten years later. In 1970, Fernando Belaúnde Terry[40] built the marginal regional highway, connecting Tarapoto to northern and coastal Peru. Migration levels exploded and soon after, the widespread production of native coca was introduced to the region as a cash crop for the production of cocaine. With the completion of the highway came improved transportation options for traffickers and increased accessibility to labor markets (UNODC 2013).

[40] Fernando Belaúnde Terry was President of Peru for two consecutive terms, from 1963-1968 and again from 1980-1985. During his first term in office, Belaúnde pushed through many development policies. He also authored a book, *La conquista del Perú por los Peruanos* in 1959, which supported the conquering of Peru, and the jungle, by and for Spanish-descendant Peruvians.

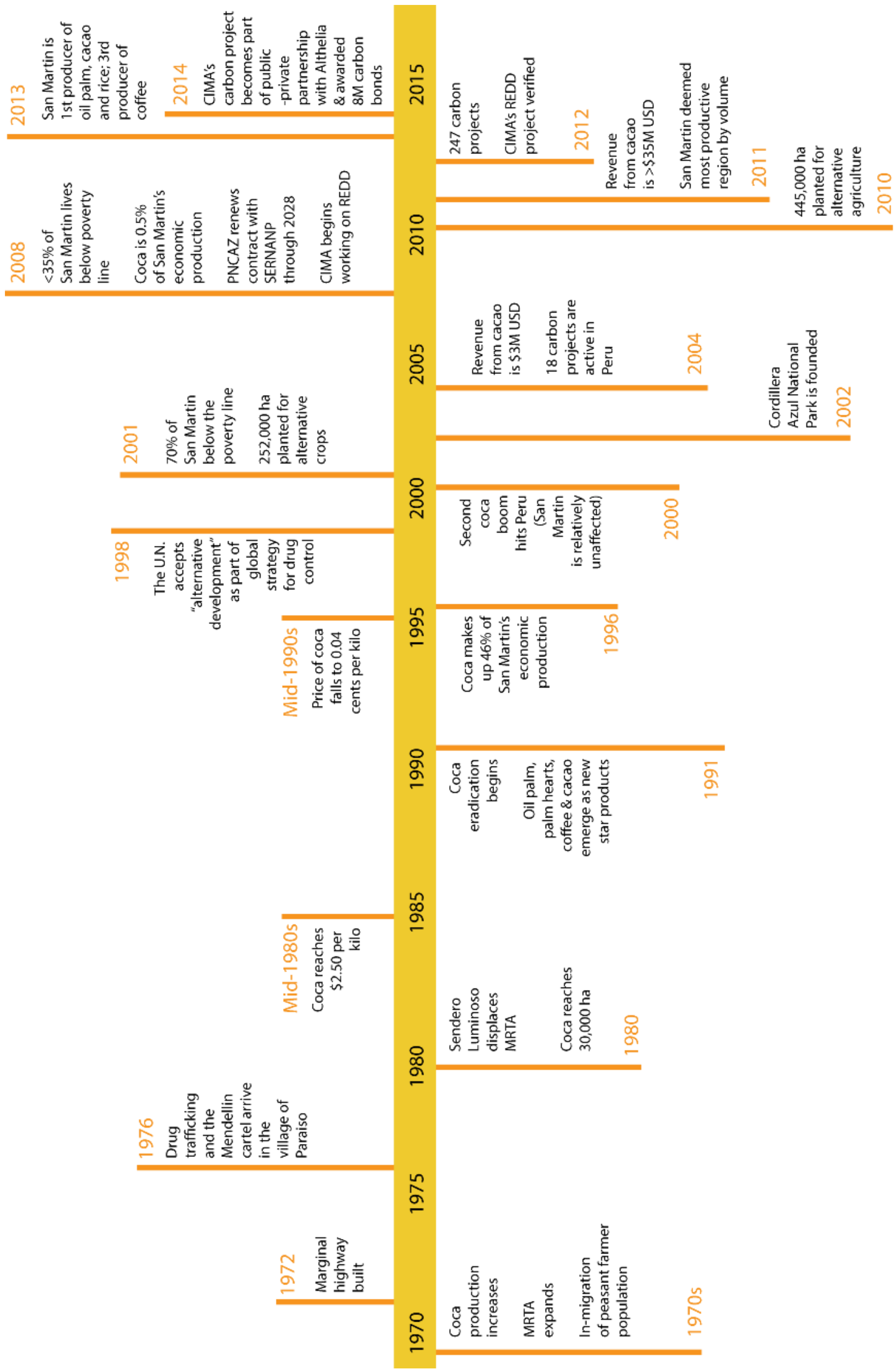

Figure A1: An economic timeline of San Martin.

While drug trafficking undoubtedly affected the entire region, the Huallaga Valley was a main hub of this activity. By 1976, trafficking had arrived in San Martin through the village of Paraiso in Tocache (see Figure 1 for map) (UNODC 2013). Colombian drug cartels dominated this coca/cocaine[41] trade, first through the Mendellin cartel and later through the Calli cartel. At the same time, the Revolutionary group, MRTA ("Movimiento Revoluncionario Tupac Amaru") began to expand across the region. In the early 1980s, MRTA was largely displaced by members of Shining Path ("Sendero Luminoso"), a Peruvian revolutionary organization that employed guerilla tactics in support of Maoism.[42]

Drug traffickers played off the insecurity left by MRTA and Shining Path. Soon San Martin was producing more coca than any other region of Peru—a country that was already considered the greatest producer of coca worldwide—by the early 1980s (UNODC 2013). A few short years later, 30,000 hectares of coca were in cultivation in San Martin. This was equal to over 290 sq. km (>115 sq. mi), and accounted for one-fifth of Peru's total coca production (UNODC 2013). With each kilo of processed product fetching \$2.50 USD, the booming coca/cocaine trade drew migrants from all over the country. Land conversion for coca/cocaine resulted in massive amounts[43] of deforestation and largely endangered many of the Huallaga Valley's native species (Young 1994, 1996, Dourojeanni 1992). Despite some alleged crackdowns on coca/cocaine during these years, politicians and institutional decisions also further enabled the drug trade, though many of these did not come to light until later.[44]

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[41] The term coca/cocaine is used here to differentiate between the illicit coca trade for the production of cocaine, and the legal production of coca for traditional use.

[42] Shining Path is known for their acts of terrorism, brutality, and violence against numerous citizens.

[43] Young (1996) estimated that most of the 223,200 hectares of hill agriculture present in the Huallaga Valley were deforested after 1975 as coca production spread through the region.

[44] Example: In 2001, scandal erupted when evidence was released indicating that both Nicolas Hermoza, commander of Peru's army from 1992 to 1998, and Vladimiro Montesinos, the ex-head of Peru's

The 1990s saw increased efforts to control the coca/cocaine industry. In an effort to control the insurgency and guerilla activity taking place, the Peruvian government moved to decriminalize coca/cocaine farmers between 1991 and 1994 (UNODC 2013). However, as the Colombian cartels were forced out, Mexican cartels moved in (UNODC 2013). To combat this new threat, Peru made large national efforts and collaborated with the U.S. government.[45] Much of San Martin's coca plantings were manually cut down. Others were sprayed with herbicides. As more and more lands fell infertile, the coca/cocaine trade crashed. By 1996, less than half (46%) of San Martin's economic production was due to coca/cocaine. The price per kilo had fallen from its high of $2.50 in the 1980s to just 0.04 cents per dollar. Eventually even other businesses—such as the discotecas, hotels, and restaurants that had sprouted up in response to the economic boom—were extinguished (Cabieses 2010). Populations dwindled. Between 1996 and 2000, 3,700 hectares of coca bush were eradicated annually on average. By 2001, 70% of San Martin lived below the poverty line due to the direct and indirect consequences of the anti-drug campaign (UNODC 2013) (Figure A1).

As more and more countries began to battle drug trafficking, international counteractions amped up. In 1998, the United Nations accepted "alternative development" as part of their global strategy for drug control. In coordination, the United States government began providing incentives for alternative development programs in the region (SCSGS 2013, Cabieses 2010, UNODC 2013). USAID initiatives aimed at helping farmers access credit to expand and support conventional crops as alternatives to coca and increase the productivity of existing farms (USAID 2012, USAID 2009). Over

intelligence service, had been receiving $50,000 for every drug-laden plane allowed to leave the Huallaga during these coca-centric years (BBC 2001).

[45] In 1998, Congress passed the Western Hemisphere Drug Elimination Act, which authorized the spending of $2.3 billion for international counternarcotic operations (H.R. 1998). Peru was one of the main country targets of the enacted bill.

the next several years, over $100 million USD were invested in Peru in the form of international cooperation, specifically for the establishment of such projects (UNODC 2013). Many believe that these alternative development initiatives in San Martin were a main driving force behind land use change in the region, and also supported San Martin's lack of involvement in Peru's second coca boom in the 2000s.[46]

As the financial gap left by coca/cocaine eventually began to be replaced by alternative development programs, San Martin began to recover economically. Farmers returned to the region. By the mid-2000s, over 235,000 hectares of land were in use for legal crops, primarily for the production of rice, palm oil, and maize (Cabieses 2010, UNODC 2013, see Figure A1).

However, incentives by the U.S. government may have had additional effects beyond coca/cocaine eradication and the establishment of alternative economic pathways (UNODC 2013). Specifically, they may have supported environmental degradation by improving market access and infrastructure—key necessities for the success of big agriculture, and also main drivers for deforestation (Barber 2014, Andersen et al. 2012, Kirby & Potvin 2007, Nelson & Hellerstein 1997). Whereas traditional farming in the area had mostly taken the form of subsistence agriculture with minimal technology and only occasional slash and burn techniques, following the coca/cocaine trade people strived for higher yields and profit (SCSGS 2013, CIMA 2012). Newly arrived farmers—often from the Andes or coast of Peru—expressed a fondness for large-scale, single-crop production (IGES 2014, SCSGS 2013, CIMA 2012, 2013). In contrast to migrants from within the region, who tend to be familiar with the ecosystem and report appreciating the

[46] This boom was headed by the Mexican drug cartels and resulted in coca increasing in the neighboring department of Huánuco from 9,000 hectares in 2000 to 18,000 hectares in 2009 (UNODC 2013). Nationally, effects were similar. In Peru as a whole, coca bush cultivation grew from 38,700 hectares in 1999 to 61,200 hectares by 2010. However, in contrast to the 1980s, much of this expansion now focused on the southern end of the country (UNODC 2013).

forest for its cultural value, most of the outside migrants reported feeling uncomfortable with the dense trees of the cloud forest (CIMA 2013). In reaction, these new arrivals often cut and burned the trees, claiming land tenure through deforestation. They then planted maize, rice, plantains or other monocultures with low startup costs and reasonably high yields, and farmed the area until the land eroded or became unfertile. Once the yields dropped low enough, they moved on to a new parcel of land and repeated the cycle (CIMA 2012, 2013, Bernardi 2005). As populations continued to swell, this pressure eventually resulted in more deforestation, land degradation and the deterioration of local water quality (SCSGS 2013, CIMA 2012).

In response to the mounting environmental pressures in San Martin, the Peruvian government began implementing zoning and protection strategies over the northern Cordillera Azul mountain range, an area stretching 2.5 million hectares between the Huallaga and Ucayali rivers (see Figure 1, Chapter 2). The area was considered the "last large, intact expanse of lower-montane forest remaining in Peru" (Alverson et al. 2001). On September 7th, 2000, nearly 1.14 million hectares were declared a "reserved zone" (*Zona Reservada Biabo Cordillera Azul*) to protect the area from agricultural expansion and timber harvesting. In addition, the 984,000 hectares of lowland forest adjacent to the zone, in the east, were simultaneously designated as permanent production forests (*Bosque de Produccion de la Zona Forestal Permanente*).[47]

While these designations offered some protection, Peruvian researchers and conservationists began to worry that the concession would attract new roads and colonization. In an effort to counteract these pressures, a three-week Rapid Biological Inventory (RBI) was carried out in 2002 by research scientists in coordination with the Field Museum of Chicago (Alverson et al. 2001). The RBI noted in detail the high

[47] Of these 984,000 hectares, 64,700 hectares belonged to indigenous communities, were designated for colonists, or were in litigation as of 2000 (Alverson et al. 2001).

diversity of both species and habitats within the park, as well as a couple dozen species that were new to science.[48] It also noted imminent threats included logging, new roads, colonization and timber removal (Alverson et al. 2001). In particular, the RBI report noted that the "disorganized expansion of small-scale agriculture" remained a prominent threat, especially from the north, and that "immediate threat" was present from the logging concessions to the east.[49]

Following this inventory and report, Cordillera Azul National Park was established at the edge of the Huallaga Valley in 2002 (CIMA 2012, see Figure A1). Today, it is Peru's third largest national park, protecting over 1.3 million hectares of forest and an additional 2.5 million hectares of buffer zone (Althelia 2015, CIMA 2012, 2013). It is home to an estimated 6,000 species of plants, 600 species of birds, 180 species of fishes, and over 80 species of large and medium sized mammal, and is often touted as a model for innovative community-park partnerships (Althelia 2015, IGES 2014).

2002-Present: The Rise of Coffee, Cacao, and Carbon

Though the establishment of Cordillera Azul National Park was a strong move for conservation, some viewed the park's creation as a barrier to economic activities. Communities in the buffer zone suffered from poverty and many blamed the park and the increased regulations over buffer zone activities. In an effort to avoid further detrimental land use, USAID and other development organizations began to re-promote traditional methods of agroforestry (USAID 2012, USAID 2009). Specifically, USAID promoted

[48] The RBI identified 71 species of mammals, 500 species of birds, 82 species of amphibians and reptiles, and 93 species of fish within the park. Twenty-eight of these were believed to be new to science. Given the rapid nature of the inventory, many more species were thought to be in existence and as of yet unobserved.
[49] While the report also stated that coca/cocaine plantations had destroyed large portions of the western mountains, it specifies that many of the fields around the Santa Lucía police base were abandoned and appeared to be reverting to forest.

coffee and cacao, two products previously considered smallholder crops. Coffee and cacao could be grown beside cassavas and other household consumption goods for sale to larger market (UNODC 2013, Cabieses 2010).

By selecting coffee and cacao as main focal crops, USAID, the Peruvian Government, and other institutions state that they aimed to promote environmental sustainability, entrepreneurship, and economic stability. Farmer cooperatives allowed small farmers to band together for larger profits, leveraging economies of scale (UNODC 2013). By 2008 the poverty rate in San Martin had decreased by more than half since 2001 with coca/cocaine production at just 0.5% of San Martin's economic products (UNODC 2013, Cabieses 2010). By 2011, revenues from Peruvian cacao farmers had grown by more than ten times—from a national total of $3 million USD in 2004 to over $35 million USD by 2011 (UNODC 2013, Cabieses 2010). The following year, San Martin was named the most productive Peruvian region by volume for cacao (Gomez et al. 2013). By 2013 San Martin remained the largest producer, and was responsible for 33% of national production (see Figure A1).[50]

Today, at least twenty-six different producers' cooperatives and community groups are actively working with coffee and cacao in Peru. Five of these operate directly in the Cordillera Azul buffer zone, and one—the Acopagro Cooperative—even targets the central Huallaga Valley (UNODC 2013). According to their website, Acopagro is "an organization of small cacao producers who produce high quality product."[51] In 2013, their work included 2,000 members and occupied a cultivated area of 6,000 hectares (UNODC 2013).

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[50] San Martin was also named the first producer of oil palm (79%) and rice (19%), the second producer of bananas and papaya (approx. 19% each), and the third producer of coffee (19%) (UNODC 2013), however much of this production occurred in areas outside of the area of interest for this study.
[51] According to ACOPAGRO's website. See *http://acopagro.com.pe/quienes-somos/* for more.

These cooperatives have been highly influential in defining recent land use change in the central Huallaga Valley. Prior to their introduction to the area (in 2003) none of the communities operating in the central valley portion of the PNCAZ buffer zone were growing cacao and only five communities were growing some amount of coffee (CIMA MUF 2003 and field data from CIMA 2015). As of early 2015, this has all changed. Figure A2, below, shows the distribution of cacao-producing communities in the central Huallaga Valley as of July 2015. Of the 23 communities for which data is available, 15 are now producing cacao as a main market product.

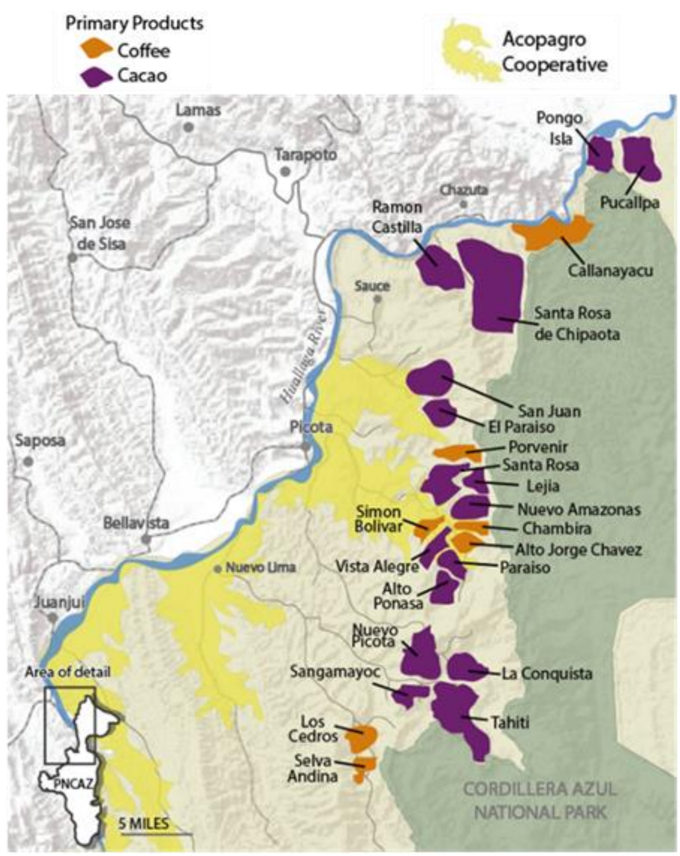

Figure A2: Coffee and cacao-producing communities, July 2015.[52]

[52] Note that given how dynamic community establishment, mobility, and titling is in the area, community names may have changed.

In addition to coffee and cacao, a third "C"—carbon—has also come to dominate the buffer zone of Cordillera Azul. As international markets for carbon offsetting grew, Peru's forests took on a new value. In 2004, the country initiated 18 carbon projects designed to pay forest managers, governments, and institutions for their efforts in avoiding deforestation or reestablishing forest ecosystems (FONAM 2012). By 2012, this number had soared to over 200 (FONAM 2012, see Figure A1). CIMA Cordillera Azul's recent award of over Euro €8 million carbon bonds (at COP20 in Lima, source: MINAM 2014) suggests that carbon is now a key component of the conservation frontier; one that will need to be balanced with the other social and ecological protections in place.

In the case of the central Huallaga Valley the balance among economic incentives, social order, and biological preservation is a delicate one. In addition to understanding the complex history of this area, there are also key theoretical and analytical dimensions to how conservation priority gets assigned. The chapter that follows will explore these through a brief overview of carbon markets, landscape ecology, and the social and economic forces at play within the study site.

THE BASIC PRINCIPLE OF ECONOMIC RENT (AND BID-RENT)

The principle of economic rent is critical to understanding the transformation of tropical forests. Simply, economic rent can be defined as any income above and beyond normal profits that is due to scarcity of a factor of production.[53] Historically this concept has taken two main pathways. The first, proposed by David Ricardo (1891)[54], suggests that rent varies due to land quality (e.g. the scarcity of high quality soil, water resources,

[53] Ricardian rent should not be confused with contract rent, which is the "actual payments tenants make for use of the properties of others" (Barlow 1986). Instead, the Law of Rent refers to the economic return that lands accrue for their use in production. Unlike profit, economic rent does not necessarily involve productive human action. It can also not be eliminated by competition, as all natural resources and locations inherently yield economic rent.
[54] Ricardo is thought to have formulated the concept in 1809, later publishing on it in his magnum opus, *Principles of Political Economy and Taxation.*

etc.).[55] The second, modified by J.H. von Thünen,[56] states that location is also a factor of production, and thus transport costs also affect rent (von Thünen 1966). This is due to the fact that agricultural prices are often given at the market center, but farmgate prices (i.e. the price the producer receives) are the result of this agricultural market price *minus* transportation costs from the farm to market. While von Thünen's model is sometimes criticized for focusing on the "isolated state" (e.g. overlooking differential transportation costs, variations in topography, site differences and chances in commodity prices), the framework of the theory is still largely considered to be relevant. For instance, distance to/from markets, distance to roads, and the type of roads nearby still largely impact the value of the land and the probability that it will be purchased and/or deforested (Barber 2014, Andersen et al. 2012, Kirby & Potvin 2007, Angelsen 1999, Omamo 1998, Nelson & Hellerstein 1997, Zeller et al. 1997).

The deforestation model presented by this study accounts for the Ricardian definition of rent through the vector of biophysical controls (i.e. soil type, precipitation, slope and elevation). It accounts for the von Thünen model[57] of land-rent through the independent variables of cost distance and Euclidean distance, respectively, based on freight cost.

Taking these two variations on rent into account, rent can be stated as:

(1) $Rent_{ik} = P_{ik}\,Q_{ik} - Q_{ik}C_{ik}$

Where P_{ik} is the price of output for use *k* at land plot *i*, C_{ik} is a vector of price inputs (i.e. average costs) to *k* at plot *i*, and Q_{ik} is the potential output quantity (modified

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55 Ricardo defined rent as equal to the economic advantage obtained by using a site (plot of land, etc.) in its most productive use, as compared to the advantage obtained when using a marginal site for the same purpose with the same inputs of capital and labor.

56 Johann Heinrich von Thünen is renowned for his great influence in developing the spatial analysis of rents, which highlighted the importance of central markets and transport.

from Chomitz and Gray 1996). In this equation, *P* and *C* are both functions of transportation cost; varying with the accessibility and location of land plot *i* and connecting rent to a spatial economy.

In addition to the concept of rent, the theory of bid-rent can also be used to understand land use decisions within the study area. If all farmers are rational, profit and utility maximizers, acting with perfect information, the theory of bid-rent assures that land is allocated efficiently, i.e. to its highest profitable use. This signifies that land use observed within the study area is, in theory, the option that results in the highest rent. If for some reason the farmer is not utilizing their land to the highest profit, they experience opportunity costs, or forgone profits due to a less efficient land use.

Assuming that all land owners are rational, profit and utility maximizers, then the theory of bid-rent states that land will naturally become allocated to its highest profitable use. For instance, if a farmer is growing corn but knows that soybeans are more profitable, the farmer will elect to change crops to increase their profit. If a farmer is growing corn, but is unaware that soybeans are more profitable, another farmer will offer to buy them out for slightly more than their current corn profits. This will continue with the farmer either choosing to change production or another party purchasing the rights to do so, until the land reaches its highest profitable use.

In the real world, economic rent and bid-rent often interact with one another. They both deal with scarcity, either of a natural resource, a quality for production, or access to markets, and they both contribute to the land's perceived value. They also tend to be correlated positively with deforestation (See Figure 2, Chapter 3).

ILLICIT FORCES IN THE CORDILLERA AZUL BUFFER ZONE

In a recent study still under review, NGO staff and government officials in San Martin report that land trafficking is common to the department, and field work for this thesis confirms this (Holland & Coomes in review, field work 2015). Defined as "a particularly aggressive form of land speculation whereby well-connected individuals and groups claim large tracts of land that are generally beyond the administrative reach of regional and local government" (Conservation International 2011 and ProCeja 2011, as cited in Holland and Coomes in review), land trafficking in the study area often involves the piecemeal selling of land (regardless of tenure) to new migrants, often from distant districts in the Sierra where people are unfamiliar with San Martin or the land being sold.

In addition to land trafficking, coca/cocaine production, illegal harvest of timber, and other illicit activities are thought to still occur in the area. While these products may be cultivated in smaller patches (see Bradley and Millington 2008 for more), their negative impact on forest health and continuity is undoubted (Young 1996). Largely untracked due to their illicit nature, the deforestation, forest degradation, and contamination that occur as a process of these activities cause undoubted harm to nearby forests, soils, waters and wildlife (Echavarria 1991, MacGregor 1990, Dourojeanni 1989).

SURVEY QUESTIONS

It should be noted that questions were written and conducted in Spanish, and were accompanied by drawings and visual aids produced by Kaitlin Tasker in coordination with CIMA Cordillera Azul.

1. ¿En qué comunidad vive?
2. ¿Desde cuándo vive acá?
3. ¿Qué cultivos tiene en su chacra?
4. ¿Cuánto terreno tiene? (Ambas áreas cultivadas y no cultivadas)
5. ¿Cuánto terreno cultivado tiene?
6. ¿Cuantas hectáreas de cacao o café tiene?
7. ¿Qué variedades de cacao o café tiene?
    a. Cacao:
    b. Café:
8. ¿Qué sistema de cultivo usa? (Cultiva asociado a árboles, cultiva en limpio, etc.)
9. ¿Cuánto pagarías por….
    a. …Una hectárea de terreno sin ningún cultivo?
    b. …Una hectárea con cultivos iniciales?
    c. …Con cultivos en producción?
10. ¿De qué depende el costo del terreno?
11. ¿Consume lo que produce en su terreno?
12. ¿Cuánto de lo que produce, vende?
13. ¿Dónde lo vende? ¿A quién lo vende? (En la misma chacra, a una persona intermediaria, a personas en la comunidad, en un centro (seco, en baba…)

14. ¿Cuánto le pagan por sus productos?

    a. En las meses de lluvia:

    b. En las meses sin lluvia:

15. ¿De qué depende el precio de sus productos? (La calidad, tiempo/clima, acceso al mercado, flete, donde fue cultivado, cantidad, etc.)

16. ¿Cuánto está produciendo ahora por su campaña?

    a. Cacao: _________________ kg/ha

    b. Café: ___________________ quintales/ha

    c. Otro producto: _______________

17. ¿Cuánto espera producir en el futuro?

    a. Cacao: _________________ kg/ha

    b. Café: ___________________ quintales/ha

18. ¿Por qué media transporta sus productos a los lugares donde los vende? (Por caballo, en camioneta por carretera…)

19. ¿En qué meses es más difícil transportar sus productos?

20. ¿Cuánto más paga por transportar sus productos en estos meses difíciles?

21. ¿Trabaja con intermediarios para la comercialización de sus productos?

22. ¿Cuánto tiempo demora para que sus productos lleguen al destino final cuando la vía de acceso está buena? ¿Y cuándo esta mala?

    a. Si se sabe el nombre de la carretera, o por donde pasa, esa información nos ayudaría bastante:

23. ¿Qué productos compra para su familia, para la alimentación diaria o herramientas de chacra? ¿Dónde los compra? ¿Y cuánto paga?

24. ¿Existen programas, proyectos, organizaciones, etc. en el área que les dan beneficios por conservar los bosques?

25. ¿Qué beneficios son? (Pagan, dan apoyo técnico, en infraestructura, etc.)

26. ¿Qué beneficios nuevos esperaría de esos programas? (insumos, asistencia técnica, que paguen, etc.)

Glossary of Acronyms

ACD	Aboveground carbon density
AOI	Area of Interest
CAO	Carnegie Airborne Observatory
CCBS	Climate, Community and Biodiversity Standards
CIMA	*Centro de Conservación, Investigación, y Manejo de Áreas Naturales* (Center for Conservation, Research, and Management of Natural Areas)
CO^2	Carbon Dioxide
ED	Euclidean distance
EDroads	Euclidean distance to roads
EDwater	Euclidean distance to waterways
FONAM	*Fondo Nacional del Ambiente* (National Environmental Fund - Peru)
GIS	Geographic Information System
LiDAR	Light Detection And Ranging (or: Light, Imaging, Detection, And Ranging)
MINAM	*Ministerio del Ambiente* (Ministry of the Environment – Peru)
m.s.l.	Meters above sea level
MRTA	*Movimiento Revolucionario Tupac Amaru*
PNCAZ	*el Parque Nacional Cordillera Azul* (Cordillera Azul National Park)
RBI	Rapid Biological Inventory
REDD/REDD+	Reducing Emissions from Deforestation and Forest Degradation
REP	Relative Effect of Population
SERNANP	*El Servicio Nacional de Áreas Naturales Protegidas por el Estado* (National Service of Protected Areas - Peru)
UNODC	United Nations Office on Drugs and Crime
USAID	United States Agency for International Development
VCS	Verified Carbon Standard

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